

Quality Improvement, Inventory Management, Lead Time Reduction and Production Scheduling in High-mix Manufacturing Environments

by

Sean Daigle

B.S., Mechanical Engineering, U.S. Air Force Academy (2015)

Submitted to the Department of Mechanical Engineering
in partial fulfillment of the requirements for the degree of

Master of Engineering in Advanced Manufacturing and Design

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Author
Department of Mechanical Engineering
January 13, 2017

Certified by
Dr. Stanley Gershwin
Senior Research Scientist
Thesis Supervisor

Accepted by
Rohan Abeyaratne
Professor of Mechanical Engineering
Chairman, Department Committee on Graduate Theses

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Abstract

This thesis is a compilation of the analysis and recommendations gathered from two industry projects conducted at Applied Materials Varian Division in Gloucester, MA and at the MIT Lincoln Laboratory in Lexington, MA. This thesis addresses the improvement of a quality metric used at Applied Materials through the means of material shortage reduction and lead time reduction of system sub-assemblies. Manufacturing quality was found to be impacted by material shortages across the facility and capacity constraints in an area of the facility that manufactures equipment sub-assemblies. Implementing a new inventory policy would result in an expected 74% to 80% reduction in material shortage occurrences. The capacity increase recommended in this thesis would reduce average lead time for sub-assemblies from about 5-6 days to under 2 days. At the MIT Lincoln Lab, this thesis addresses a possible approach to improving the accuracy of production scheduling and delivery date quotes through the use of job shop scheduling software and historical data analysis. The recommended fabrication request delivery date prediction process involves using a scheduling software to find the optimal delivery date for a job, and then adding a Shop Capacity Buffer time that is calculated using historical data on schedule delays. Schedule delays can be caused by a variety of random events that occur in machine shops, such as machine failures or operators falling ill. By selecting a Shop Capacity Buffer of 90%, a 90% on-time completion rate should be observed. This new method would achieve improved results from the 75% on-time completion rate at present. The final recommendation is a policy change that aims to characterize sources of delay and accurately compensate for the delay using the Shop Capacity Buffer in the delivery date quote process.

Thesis Supervisor: Dr. Stanley Gershwin
Title: Senior Research Scientist

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Contents

1	Introduction	13
1.1	Applied Materials Varian Division	14
1.2	MIT Lincoln Laboratory	15
1.3	Thesis Organization	15
2	First Pass Yield Quality Program at Applied Materials Varian Di- vision	17
2.1	Calculating FPY	19
2.1.1	A Secondary Metric	20
2.1.2	Example FPY Report	20
2.2	The Current Bucketing Approach	20
2.2.1	Strengths and Weaknesses of the Approach	23
2.3	FPY Sensitivity Analysis	25
2.4	Problem Approach and Statistical Tests	31
2.4.1	MIT UES Cycle Time Project	32
2.4.2	Effect of Shortages on Quality	34
2.4.3	Data Shortcomings	35
3	Critical Shortages Project	37
3.1	Current System and Procurement Types	37
3.1.1	2-Bin Kanban System	37
3.1.2	Gold Square System	41
3.2	Demand Characterization and Curve Fitting	41

3.3	Reorder Point Selection Using Two Plausible Distributions	42
3.3.1	Theoretical Discussion	42
3.3.2	Applying Inventory Methods	47
3.3.3	Recommendations and Results	49
4	Supermarket Lead Time Reduction Project	51
4.1	Value Stream Mapping	51
4.1.1	Present and Future State Analysis	52
4.1.2	The Varian Supermarket Current State Map	54
4.1.3	Supermarket Ideal State Value Stream Map	56
4.2	Capacity Constraint Analysis	58
4.2.1	Goals and Methodology	59
4.2.2	Summary	67
5	Model Based Engineering Project at the MIT Lincoln Lab	69
5.1	Future State: The Model Based Enterprise	70
5.1.1	Relevant Requirements	72
5.1.2	Production Environment and Scope	73
6	Lincoln Lab Shop Scheduling and Capacity Planning	77
6.1	Proposed Methodology for Improving Delivery Quote Accuracy	77
6.1.1	The Current Quoting Process	78
6.1.2	General Quoting Ideology	79
6.2	Data Collection	79
6.3	Simulation and Data Analysis	84
6.4	Process Change and Recommendations	88
6.4.1	Conclusions	90
7	Summary and Conclusions	91
7.1	Applied Materials Varian Division	91
7.2	MIT Lincoln Laboratory Engineering Groups	93

List of Figures

2-1	First Pass Yield 2011 to Present.	26
2-2	QN/mod vs. FPY Conceptual Relationship	27
2-3	A Moving QN/mod Probability Distribution	27
2-4	UES Monthly QN/mod Distributions	28
2-5	UES Monthly QN/Mod vs. FPY Data Points 2011-2015	29
2-6	Monthly QN/Mod vs. FPY Data Points 2011-2015	29
2-7	Monthly QN/module Distribution Before and After MIT UES Critical Path Project	33
2-8	Scatter Plot of Part Shortages vs. QNs on a Tool for 2015-2016	35
3-1	Shortage Counts Relative to Number of Parts on Tool	39
3-2	Example Geometric Daily Demand Fits	43
3-3	The Parameters of the Negative Binomial Distribution	45
3-4	Negative Binomial Cumulative Distribution Function	45
3-5	Example Weekly Demand Distributions and Model Verification	46
4-1	Current State Supermarket Value Stream Map	55
4-2	Ideal State Supermarket Value Stream Map	57
4-3	Backlog Summary with Recommended Workforce Structure	62
4-4	Simulation Summary with Recommended Workforce Structure	64
4-5	Recommended Certifications by Assembly, Per Shift	66
4-6	Recommended Workforce Size	66
6-1	Current Completion Date Quoting Process	78

6-2	Process Time Estimate Error 2014 - Present	80
6-3	Process Time Error Distributions	81
6-4	Highly Utilized Workstations Visited vs. Delay From Optimal Schedule	85
6-5	Anticipated Delay Prediction Interval Plot	87

List of Tables

2.1	FPY Sample Calculation - Module FPY	19
2.2	FPY by Module for December 2015.	21
2.3	FPY by Module for January 2016.	21
4.1	Production Forecast Format	59
4.2	Supermarket Certifications Matrix	60
4.3	Queue Time Summary	65
6.1	Results: Upper Bound of Shop Capacity Buffer Estimates	86

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Chapter 1

Introduction

This thesis is a compilation of two industry projects carried out by the Master's candidate at two separate locations. This thesis presents the analysis and summary of these projects with detailed presentation of the significant findings and contributions. The two locations of interest in this paper are 1) the Varian Division manufacturing facility run by Applied Materials, Inc. (Nasdaq: AMAT) located in Gloucester, MA, and 2) the fabrication shop run by the MIT Lincoln Laboratory in Lexington, MA. While these projects are unrelated to one another, both manufacturers perform the fabrication and assembly of high-cost precision equipment. Both manufacturers operate in a low volume, high-mix environment. The problems these types of manufacturers encounter are often quite different than the problems that mass production manufacturers experience.

The work carried out at Applied Materials Varian Division was completed as part of a team of MIT Master of Engineering in Advanced Manufacturing and Design students. Individual and group work is presented in these sections. The MIT Master of Engineering team consisted of Shaswat Anand, Sean Daigle, and Elyud Ismail. Anand and Ismail's theses are cited in the citations section of this paper [1][2]. The project described here that took place at the MIT Lincoln Laboratory is work completed by only this author.

1.1 Applied Materials Varian Division

Applied Materials, Inc. is a global leader in providing innovative equipment, services and software to enable the manufacture of advanced semiconductor, flat panel display and solar photo-voltaic products. Applied Materials purchased Varian Semiconductor and their ion implantation equipment manufacturing facility in Gloucester, MA in 2011. The Varian division of Applied Materials produces a variety of product lines all involved with semiconductor wafer processing and handling.

Ion implantation is one of the most widely used processes for doping semiconductor wafers in order to give the wafer its desired electrical properties. While the science of silicon wafer processing is not central to this thesis, a limited understanding of this process is necessary to understand the wafer processing equipment quality improvement program discussed in this thesis. The process of doping a silicon wafer involves presenting the wafer to a focused and filtered ion beam. The beam begins as an ionized gas and is focused through a series of magnets that propel the ions around a beam-line path eventually arriving at an end processing chamber. It is this series of magnets that filters the undesirable charged particles from the beam by directing the beam around around two corners. By directing the ions around the beam line corners, only the ions of the desired charge and weight remain by the time the silicon wafer is exposed to the beam. The equipment that focuses the ion beam is quite large and complex, and is mostly hand assembled. Almost all assembly takes place at Applied Materials Varian Division in Gloucester. While there is not any material cutting or shaping taking place in Gloucester, many sub assemblies to the larger ion implantation equipment are built up from tiny piece parts assembled on workbenches. The Varian Division could be best described as an assembly plant building a variety of products.

1.2 MIT Lincoln Laboratory

The MIT Lincoln Laboratory is a federally funded research and development center that applies advanced technology to problems of national security. A Federally Funded Research and Development Center (FFRDC) is a not-for-profit organization funded by the U.S. Government to meet long-term research and development needs that cannot be met as effectively by existing in-house or contractor resources. Research and development activities focus on long-term technology development as well as rapid system prototyping and demonstration. The Laboratory works with industry to transition new concepts and technology for system development and deployment. Two of the Laboratory's principal technical objectives are (1) the development of components and systems for experiments, engineering measurements, and tests under field operating conditions and (2) the dissemination of information to the government, academia, and industry.

The first of the Laboratory's principal objectives involves the fielding of advanced hardware for engineering tests, technology capability demonstrations, and increasingly, the larger scale manufacture of some systems at the request of the sponsor organization of the research. In order to meet these needs, the Lincoln Laboratory has outfitted itself with highly capable mechanical and electronic fabrication shops. These shops are capable of fabricating and assembling anything from satellites to laser communications systems in low volume.

1.3 Thesis Organization

This thesis is organized as follows: Chapter 2 outlines the projects carried out at Applied Materials Varian Division as a part of the First Pass Yield Quality Program. Chapter 3 discusses the inventory management project taken on by the team of MIT Master of Engineering in Advanced Manufacturing and Design students in an effort to reduce shortages leading to quality issues. Chapter 4 discusses the Supermarket Lead Time reduction project also carried out at Applied Materials as part of an effort to

reduce the necessary inventory carried while still meeting production demand. Chapter 5 introduces the Model Based Enterprise project at the MIT Lincoln Laboratory. Chapter 6 details the Production Scheduling and Capacity Planning project carried out at the Lincoln Lab. Chapter 7 summarizes the conclusions and recommendations presented through chapters 1-6.

Chapter 2

First Pass Yield Quality Program at Applied Materials Varian Division

As discussed in Chapter 1, Applied Materials Varian Division is a global leader in the design and manufacture of wafer processing equipment for the semiconductor industry. The ion implantation equipment assembled at the Varian Division facility in Gloucester is shipped to the customer site in what Varian calls modules. Modules are large assemblies that can be assembled in the wafer fab setting at the customer to facilitate easier shipment. These modules are manufactured and shipped as individual units, and are tested only at the module level. They are not usually assembled and tested as a completed ion implantation tool until deployed at the customer site. Postponing final assembly to the customer site makes it imperative to test each and every module at the end of its build so that the whole tool works upon integration. When one batch of wafers can cost well over a million dollars, the quality and reliability of the manufacturing equipment is paramount and warrants 100% inspection of the module units. Smaller sub-assemblies to the module units are assembled in what Varian calls the Supermarket area. The Supermarket is a combination piece part storage location and designated build area for the smaller sub-assemblies that are integrated into the module units. The equipment built in the Supermarket is also tested at the sub-assembly level to ensure easy integration into module units. It should also be noted that Supermarket assemblies can be sold directly to the customer

as replacement assemblies or as part of scheduled maintenance for the module units.

As part of a successful continuous improvement program to minimize equipment failures and ensure high manufacturing quality, the Varian manufacturing facility in Gloucester implemented a First Pass Yield (FPY) quality program in 2011. The greater motivation behind the First Pass Yield program at Applied Materials is continuous quality improvement. First pass yield itself as a term comes from the manufacturing principal that the proportion of the units coming out of the manufacturing process that are operational without any rework or scrap should be maximized. First pass yield is normally defined as the proportion of fully operational units produced without defects that do not require rework as a ratio of the total throughput for some time period.

$$\text{First Pass Yield} = \frac{\text{Operational Units Produced Without Rework}}{\text{Total Units Produced}} \quad (2.1)$$

At Applied Materials Varian division, the unit size being shipped is the module. Therefore, First Pass Yield is measured at the module level. Module level FPY is the proportion of modules that are built without a quality notification being written against the module. A Quality Notification (QN) is the standard documentation of a workmanship error, supplier part defect, damaged part, etc. at Applied Materials. A QN is written at each abnormal quality occurrence. A single QN written against a module designates the module as defective and counts against the First Pass Yield metric. The purpose of the existence of the First Pass Yield team is to reduce the number of defects, and therefore Quality Notifications, that are attributed to *manufacturing error*. While the intricacies of all the sources of QNs are not within the scope of this paper, the reader should understand that supplier defects, late delivery, etc. do not count against First Pass Yield. Only errors that occur within Applied Materials Varian Division during the build process are counted in this metric.

The First Pass Yield program at Applied Materials Varian Semiconductor resulted in a significant reduction in number of defects per module across all the modules following project inception. First Pass Yield increased from around 55% across all

modules in the fiscal year 2011 to about 80% in 2013, but has remained stagnant since. One of the primary goals in bringing in a group of MIT Master of Engineering students (henceforth referred to as the MIT team) was to ascertain reasons for this stagnation of FPY, critique Applied Material's FPY program and present Applied Materials with a methodology that improves yield in the future.

2.1 Calculating FPY

Any quality issue found during the process of build or testing of a module is logged in as a Quality Notification (QN) in the ERP (SAP) system. Therefore, the electronic ERP database is the method of documenting defects at Applied Materials. The FPY program has several managers assigned to the improvement effort. Most notably, the manager that is the head of each module's assembly line is present at the meeting. Any further reference to the FPY Team will be a reference to this group of individuals.

The FPY for any particular module for a time period is defined as the ratio of the number of modules built without any quality defect without rework to the total number of modules built in that period. While this calculation may be simple for one type of module, the First Pass Yield metric is the combined FPY statistic across all module types being built that month in Gloucester. The overall ion implantation machine first pass yield is calculated by weighing the module FPY by the number built of each module type. An example calculation of module FPY is shown in table 2.1.

Module Type	No. of Modules Built	No. of Modules without QNs	Module FPY %
A	x	u	$\frac{u}{x}$
B	y	v	$\frac{v}{y}$
C	z	w	$\frac{w}{z}$

Table 2.1: FPY Sample Calculation - Module FPY

Extending this definition, we calculate the FPY for the ion implantation tool as the

weighted average of the individual modules' FPY in equation 2.2.

$$FPY = \frac{(\frac{u}{x} \times x) + (\frac{v}{y} \times y) + (\frac{w}{z} \times z)}{x + y + z} = \frac{u + v + w}{x + y + z} \quad (2.2)$$

2.1.1 A Secondary Metric

Another metric often used at the module level of analysis is the QN/module metric. QN/module is calculated as the number of QNs against a type of module divided by the throughput for the type of module. While the two metrics, FPY and QN/mod are highly linked, they are not necessarily inversely related as multiple QNs can fall on the same module. Such a situation would adversely affect the QN/mod metric, but not the First Pass Yield.

$$\frac{QN}{Module} = \frac{\text{No. of QN}}{\text{No. of Modules Built}} \quad (2.3)$$

2.1.2 Example FPY Report

At the start of the FPY project meeting that begins a month, the previous month's numbers are displayed to the FPY Team. The format for this presentation can be seen below in tables 2.2 and 2.3. The two tables show counts of all the modules manufactured in the months of December 2015 and January 2016. They show how each module's FPY is affected by the QN count. Of significant importance on from these tables is the low first pass yield on both the 90 Module and UES Module relative as compared to all other modules.

2.2 The Current Bucketing Approach

The current method of reporting Quality Notifications is through direct worker input by logging the QN into SAP on the factory flow line. After a quality incident is

Location	Total Build	Passed	# Defects	% FPY	Average QNs/Module
55/70 Mod Assy/Test	9	8	1	89	0.11
90 Mod Assy/Test	9	6	8	67	0.89
Facilities Mod Assy/Test	9	9	0	100	0.00
Gas Box Mod Assy/Test	9	9	0	100	0.00
MC Term Assy/Test	2	2	0	100	0.00
MC BL Assy/Test	2	2	0	100	0.00
UES Mod Assy/Test	11	2	15	18	1.36
Final Assembly/Shipping	10	10	0	100	0.00
Final Test	3	3	0	100	0.00
Buffer	10	10	0	100	0.00

Table 2.2: FPY by Module for December 2015.

Location	Total Build	Passed	# Defects	% FPY	Average QNs/Module
55/70 Mod Assy/Test	14	12	3	86	0.21
90 Mod Assy/Test	14	6	12	43	0.86
Facilities Mod Assy/Test	14	14	0	100	0.00
Gas Box Mod Assy/Test	14	14	0	100	0.00
MC Term Assy/Test	6	4	2	67	0.33
MC BL Assy/Test	6	6	0	100	0.00
UES Mod Assy/Test	20	6	25	30	1.25
Final Assembly/Shipping	20	20	0	100	0.00
Final Test	4	4	0	100	0.00
Buffer	20	20	0	100	0.00

Table 2.3: FPY by Module for January 2016.

observed, the worker writes a QN in SAP at some point throughout the day before departing. A large proportion of quality incidents are not found during assembly, but during test. In this case the test technician logs the Quality Notification into SAP. The Quality Notification electronic form in SAP includes fields such as the part number that failed, time to diagnose, time to repair, worker responsible (if known) and a description section. Images can also be attached. After logging the quality notification, the worker's job in the Quality Notification process is put on hold. The Quality Engineering team is then responsible for addressing the QN. The Quality Engineering team will then determine whether the QN should be grouped into one of many types of QNs. There are QN types that correspond to manufacturing (workmanship) quality, supplier quality, material handling, material unavailability, and many others. As previously mentioned, the First Pass Yield project is concerned with Quality Notifications pertaining to manufacturing (workmanship) quality. If the QN does get classified as a manufacturing quality issue, the First Pass Yield team investigates each and every QN assigned to this category.

Within the Quality Notification (QN) cause code of manufacturing, there are 4 sub-categories henceforth referred to as buckets. These buckets are as follows:

1. Connections
2. Harnessing
3. Vacuum
4. Parts

Connections refers to mis-connections and loose or faulty connections of the air, water, gas or mechanical nature. Harnessing refers to mis-connections or loose or faulty connections of the signal or electrical nature. Vacuum refers to any sort of failure mode that causes a vacuum chamber on the ion implantation equipment to fail. Parts failures is a larger category that encompasses broken parts during installation, fried or dead on arrival circuit boards or computers, and wrong settings or misused parts.

When the First Pass Yield team began their initiative in 2011, the team saw that these four categories made up the vast majority of their manufacturing failures. The team created the four categories and assigned four bucket leaders the responsibility for investigating failures with his or her bucket. These bucket leaders are the manufacturing floor managers that make up majority of the FPY team.

Investigating a quality notification as a bucket leader is a weekly event that is time consuming and thorough. Each bucket leader is assigned his portion of the previous week's QNs from the Quality Engineering team. The leader then investigates the QN by talking to the workers on the shift that observed or created the defect, examining the possible causes of failure, and identifying any extenuating circumstances to bring up during the weekly First Pass Yield meeting that takes place on Wednesday. At the heart of this investigation is the goal of finding the root cause of the failure and proposing procedures, redesigns, or changing the assembly sequencing to mitigate the risk of future failures. The entirety of the FPY team as well as the individual bucket leader have a discussion during the FPY meeting as to whether a procedure change or other mitigation method is required to prevent future failures. The team also determines whether the cost of procedure change or equipment redesign is too high relative to the cost of failure to justify action.

2.2.1 Strengths and Weaknesses of the Approach

The approach detailed here is the approach that has been followed by the FPY program since its inception. Significant improvement was shown in the initial years of the project. The bucketing approach led to numerous improvements in all the buckets which had a combined positive impact on the FPY. Using this approach, failures that clearly fall within a bucket are easily identified. Trends can quickly be observed as multiple QNs written against a part number can be easily recalled in SAP. The FPY team composition of Quality Engineers and manufacturing floor leaders makes it such that the root cause of many issues can be identified. Once identified, the team can then make the ultimate decision of whether to revise an assembly procedure, design a new test procedure, implement a new failure mitigation step into the build sequence,

or even redesign the structure being assembled to prevent future failures. Of course, the cost of the failure and the number of failures over the product history are weighed relative to the cost of implementing a permanent fix to the problem.

Despite the seemingly complete and exhaustive approach of investigating every manufacturing QN observed each week, this method has not been successful to reduce the FPY numbers in recent history. The MIT team of Anand, Daigle and Ismail developed a concern over the course of this project that this method may be overly specific. Ismail discusses in his thesis [2] that this approach easily identifies repeating part numbers that have failed, yet does not identify parts of a similar family that have failed if they do not share the same part number. Ismail outlines a new method that groups failures into functional categories that classify the failure observed by failure mode. For example, a fiber optic signal cable that connects analogue digital input/output (ADIO) units can fail by being damaged, misconnected, loosely connected, or be forgotten to be connected. Each of these modes of failure require different solutions to mitigate the failure. However, the existing First Pass Yield bucket approach would group all of these failures into one category: Connections. Likewise, vacuum seal failures caused by dust particles vs. stray strands of hair vs. a scratched o-ring surface require drastically different projects to address the root cause of the failure. Ismail suggests creating separate categories for these many different failure modes as he believes a functional category should assist the FPY team in arriving at a fix for each category as opposed to merely dividing up weekly work between bucket leaders as is the case with the current bucket approach [2].

Another major weakness of this approach is that without a common failure mode, many of the manufacturing defects experienced seem like they have no root cause other than lack of attention to detail on the assembler's part. While it is true that all misconnections are misconnected by the assembler in this environment, the aim of the manufacturing engineer is to find a root cause and fix the problem as opposed to assigning blame. Using the five why's (a common Lean/Six Sigma technique) helps the engineer identify the root cause of an issue and find fixes to solve the problem. During the FPY weekly meeting, Anand, Daigle and Ismail observed that many

of the QN's were being dismissed as "attention to detail." Dismissing an issue as attention to detail should never be acceptable as this does not remedy the problem, and the quality notification could show up again and continue to adversely affect quality. While it is acceptable to conclude that the fix to a problem is too expensive relative to the cost of the quality issue, root cause should always be assigned and the decision to not take action should be documented. The current bucket approach, while effective at the start of the FPY program, is no longer steering the FPY team towards effective solutions, but leaving them to assign blame on the worker. It is for these reasons that the MIT team of Anand, Daigle and Ismail recommend "re-bucketing" and assigning QN's to categories of common failure mode. For a detailed explanation of this recommendation, see the thesis written by Ismail [2].

2.3 FPY Sensitivity Analysis

The FPY team has been recording data on the monthly First Pass Yield since the start of the project in 2011. The MIT team began by examining the existing data set for direction as to any trends and to identify the effects of previous FPY projects on the metric. Historical First Pass Yield improvements can be seen in figure 2-1. While marked improvement was observed from fiscal years 2011-2013, yield has remained stagnant since. The dotted line represents the First Pass Yield goal for the year. The goal is set by the FPY team to be attainable, as this is a business unit that will be graded against their goal by higher management. Upon observing that FPY numbers were becoming stagnant, the FPY team no longer set ambitious goals for improvement, which is reflected in the stagnation of both the goal and results in figure 2-1.

The MIT team of Anand, Daigle and Ismail realized in the early weeks of this project that the FPY and QN per module relationship was not strictly inversely proportional. The relationship is instead defined by the binary nature of passing module test. There are two outcomes to passing module test - either pass or fail. However, it is the average of the modules that pass and those that fail that creates

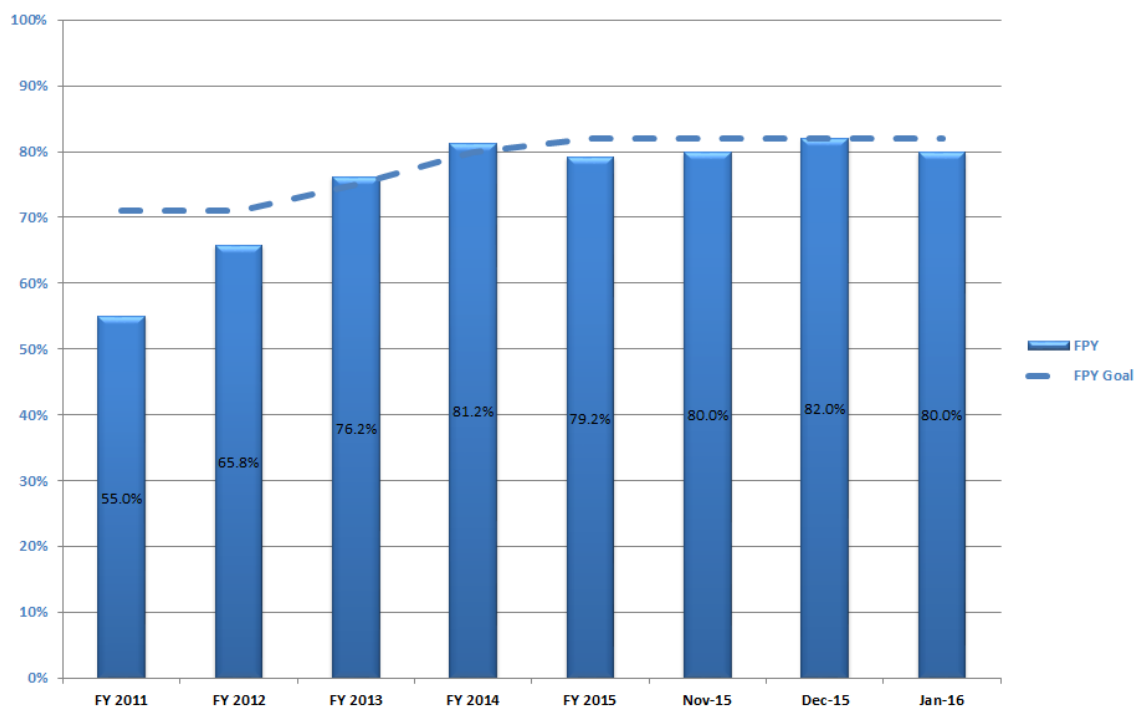


Figure 2-1: First Pass Yield 2011 to Present.

the First Pass Yield metric for the month.

According to Douglas Montgomery, a random variable that arises frequently in statistical quality control is the number of defects or nonconformities that occur in a unit of product [3]. The probability density function of such a random variable is Poisson distributed. Poisson distributions, while normal looking, are of a different nature and are skewed from normal. The principle remains the same however that the variable defects per module (QNs/mod) has an expected value and a probability distribution for each type of module.

Stemming from the idea of viewing QNs/module as a random variable with its own distribution, a theoretical relationship between QNs/mod and FPY was drawn. As module yield is a pass/fail designation, the expected value for defects per module must be below 1.0 to have consistently high yield over many modules. Just how far below 1.0 is necessary is dependent on the shape of the probability distribution of errors, which is given by the nature of the assembly process for the module. This relationship is illustrated conceptually in figures 2-2 and 2-3. Figure 2-2 shows that

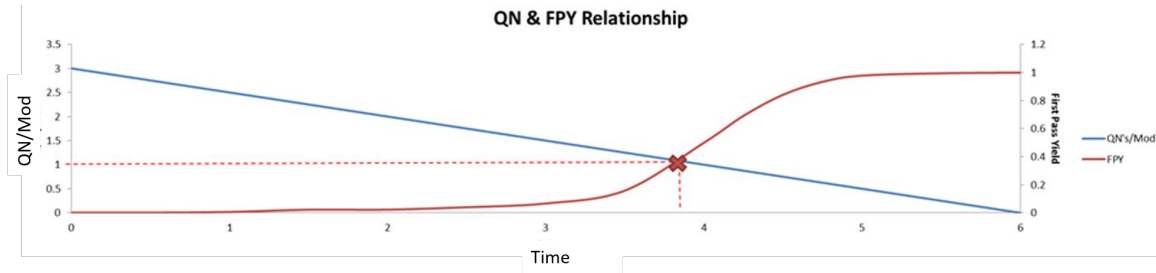


Figure 2-2: QN/mod vs. FPY Conceptual Relationship

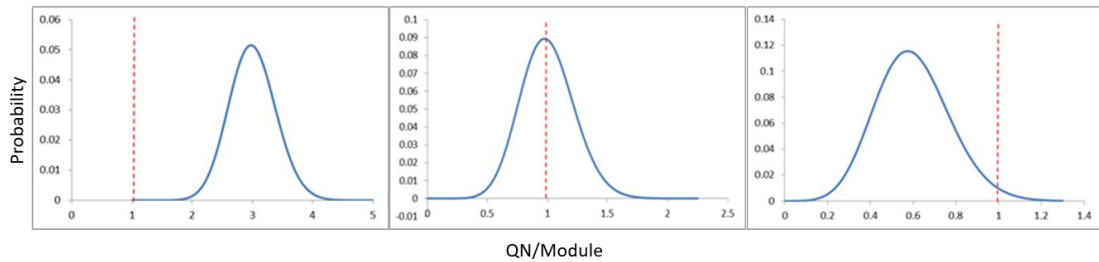


Figure 2-3: A Moving QN/mod Probability Distribution

as the average number of QNs/mod is improved at a constant rate, FPY does not increase constantly, but increases dramatically as the expected error rate (QN/module) approaches and 1.0. Figure 2-3 shows the error rate probability distribution sliding left with the expected number of errors on the x-axis falling to below 1.0. These figures help describe the idea that FPY increases rapidly as the mean of the QN/module probability distribution approaches 1.0 QNs/mod, and that if the probability distribution lied entirely below 1.0, FPY would be nearly perfect.

The MIT team sought to verify the true nature of the error rate of the modules being produced at Applied Materials. Plotting histograms of the monthly average QN/module count on the universal end station module across multiple years validated the idea that the error rate has an associated probability distribution. Sample histograms of the average QN/module count for the 12 months of 2012 and 2015 are shown in figure 2-4. On these figures, the mean is represented by the light red line. A shift of the mean downwards from about 1.65 QN/mod to about 1.25 QN/mod took place over this 3-year period.

A final manipulation of the data published by the First Pass Yield team showed the effect of quality improvement over time on the company's First Pass Yield. The

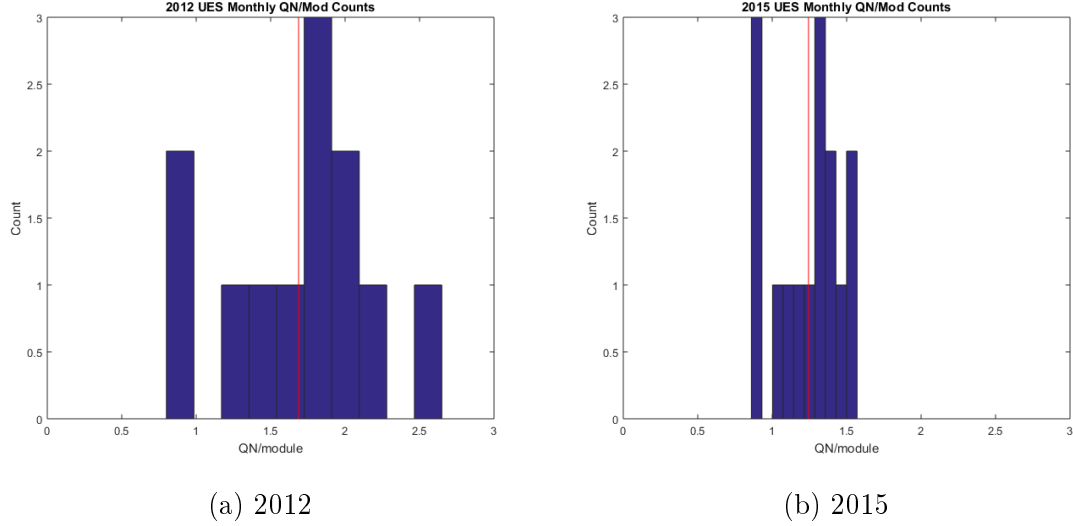


Figure 2-4: UES Monthly QN/mod Distributions

QN/mod count for all months from 2011 to 2015 were plotted as a scatter plot point against the corresponding month's FPY on the dependent axis in figures 2-5 and 2-6. The resulting plots showed that improvement in the goal variable of First Pass Yield is not linear. These figures show with real historical data the increasing rate of return on FPY by decreasing the number of QN/mod to below 1.0. The points plotted in red in figure 2-5 and 2-6 represent the most recent 12 months in 2015.

A basic form fit to the data was created out of hope to eventually provide a future forecast to the First Pass Yield team on the FPY they could achieve given X amount of improvement in quality. While a full model was not built due to missing data on the number of total failure opportunities, (the variable N in equation 2.4) the model is worth discussing as it helps clearly define the not-so-intuitive relationship between QN/mod and FPY. In the following equations, N is number of opportunities for failure on a module. In this situation, this is the number of manual assembly steps that could result in mis-assembly, such as driving a screw, sealing a vacuum chamber, or making a signal connection. Q is the probability of failure at each opportunity. While a more advanced model would distinguish between the difficulty of the various assembly steps, this model implies a lumped probability of failure. In this model, n is the number of failures observed in a period of time (the QN count), and \bar{n} is the

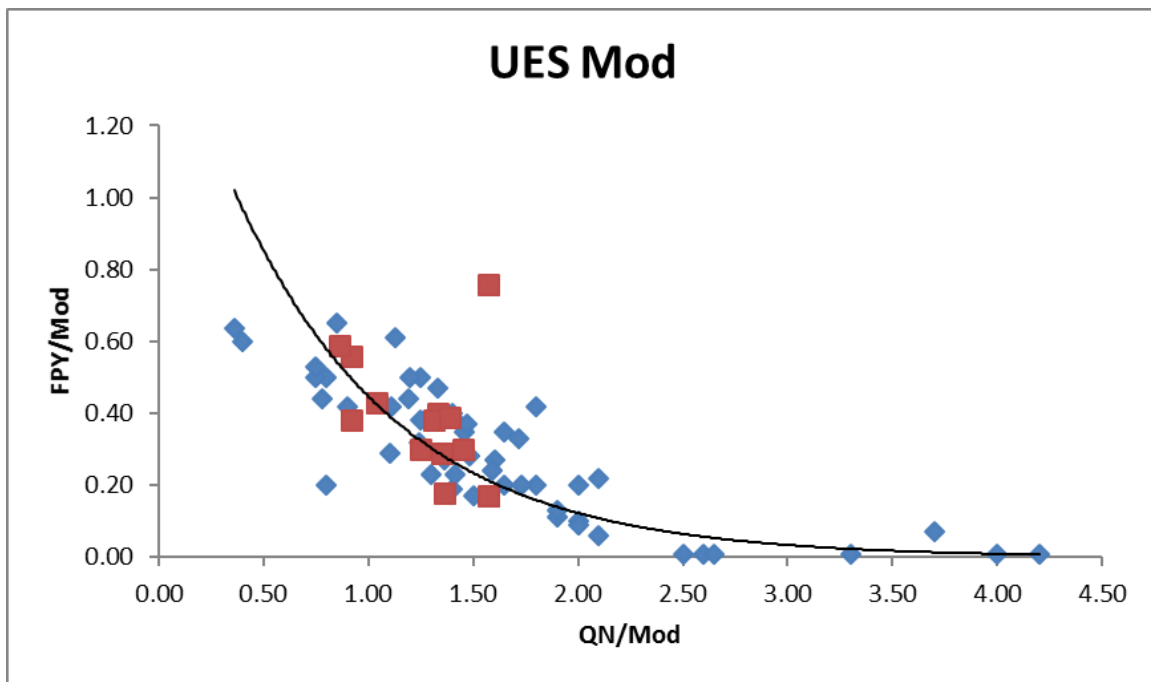
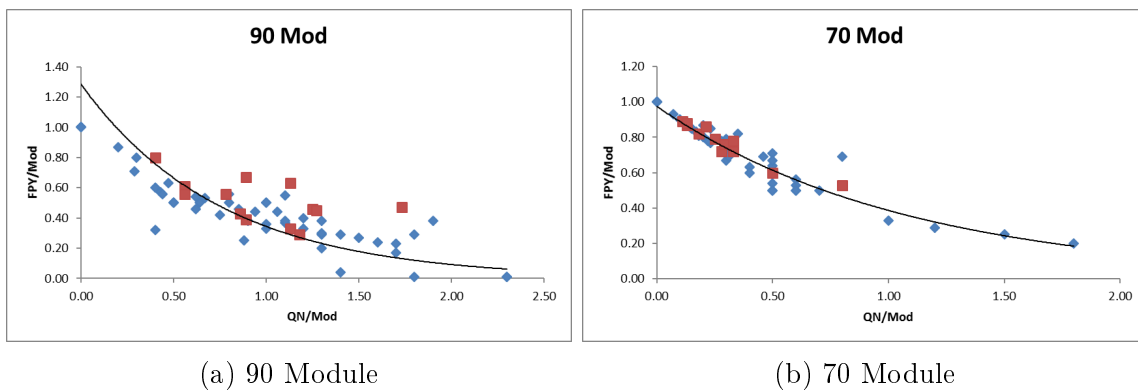


Figure 2-5: UES Monthly QN/Mod vs. FPY Data Points 2011-2015



(a) 90 Module

(b) 70 Module

Figure 2-6: Monthly QN/Mod vs. FPY Data Points 2011-2015

average or expected number of failures for that time period. Finally, m is the number of modules built over the time interval.

It follows that:

$$\bar{n} = E(n) = Q \times N \quad (2.4)$$

Then, the probability of having zero (0) failures would be

$$P(0failures) = (1 - Q)^N \quad (2.5)$$

Given that the number of opportunities for failure on that module type for the whole month is $N \times m$, then by substitution, FPY is the probability of having zero failures across multiple (m) module builds.

$$FPY_{mod} = \left(1 - \frac{\bar{n}}{N \times m}\right)^{N \times m} \quad (2.6)$$

As we know, the negative exponential function has a similar form:

$$e^{-x} = \lim_{k \rightarrow \infty} \left(1 - \frac{x}{k}\right)^k \quad (2.7)$$

Based on the similarity and supporting data, Anand, Daigle and Ismail are confident that module FPY follows some form of exponential fit. If $N \times m$ is large, as would be expected when it comes to building complex machinery, the FPY equation can be simplified to equation 2.8.

$$FPY_{mod} \approx e^{-\bar{n}} \quad (2.8)$$

While this model is of interest in an academic sense, it can be used to provide direction in an effort to improve Applied Materials' bottom line. Looking back at tables 2.2 and 2.3, it is clear that there are only two modules that are relatively close to 1.0 in average QN's per mod over a month. The majority are close to zero. Such a situation means mathematically, that the most efficient way to improve this metric

is to focus solely on the 90 module and UES for improvement projects. Moving the expected QN/module count down yields exponential rate improvement in module FPY when crossing below the 1.0 QN/mod mark and very little FPY improvement when QN/mod changes occur far above or below the 1.0 mark.

2.4 Problem Approach and Statistical Tests

This MIT Co-op's general approach to finding new improvement methods for reduction of the defect (QN count) was through the use of a hypothesis tree. At the highest level, the hypothesis tree is a cascading problem-focused effort to reach individual, testable problem statements that provide direction for the improvement effort. At the top of the tree begins with the simple statement *first pass yield is too low*. This is followed by the statement *QN's/mod are too high*. Intermediate hypotheses included: *Errors fall disproportionately on certain types of modules*, and *inexperienced workers create more QN's than their experienced counterparts*. The best hypotheses are those that were directly testable with the data at hand. Some hypotheses that were tested that did not show statistical significance included:

- Lengthy build times increase risk of QNs due to greater exposure time for errors
- Inexperienced workers create more assembly errors than their experienced counterparts
- Workers are unable to see debris due to lighting and magnification needs while cleaning vacuum surfaces

Successful hypothesis tests included:

- Changing the assembly sequence can affect the error rate
- Certain buckets of errors create more QNs than other error buckets
- Part shortages cause assembly steps to be performed out of the order specified in the assembly instructions, leading to more QNs

The method for testing these hypotheses was by using data before and after a historical improvement project or procedure change, and testing whether the change had a significant effect using ANOVA.

2.4.1 MIT UES Cycle Time Project

The 2014 MIT Master of Engineering in Manufacturing project took the existing build procedures and performed a critical path analysis to determine the optimal assembly sequence for the Universal End Station (UES). The project reduced the build time per UES module from about 5 days to 2.5 days at full manning (5 assemblers). While the project largely shuffled around major assembly steps to advance the critical path, the project also broke the existing material delivery kits into 21 kits from 12, and added additional standardization to the procedures by very specifically calling out material locations and specifying exactly the start and stop points for a particular assembly step.

The data showed an interesting conclusion when examining the monthly QN/mod count for the 12 months before and after the MIT project implementation. While the mean QN/mod count did not shift significantly before and after the project, the variance of the count of monthly QN/module did change significantly. Figure 2-7 shows the boxplot of the effect on the monthly QN/module distribution before and after the MIT UES critical path project.

An F-test was performed on the 12 months before compared to the 12 months following the MIT UES critical path project to capture the significance level. The F-statistic for 95 percent confidence and 12 data points in both samples is 2.69. The ratio of variances in this data set is 3.91. Therefore, the MIT critical path project had a significant impact on the variance of the UES error rate to the 95 percent confidence level.

The conclusion that assembly sequence could impact quality suggested to Anand, Daigle, and Ismail that the assembly sequence for a module could be optimized for quality as opposed to cycle time. While build path optimization for quality (ease of assembly) seemed like a promising area, the group decided against pursuing this

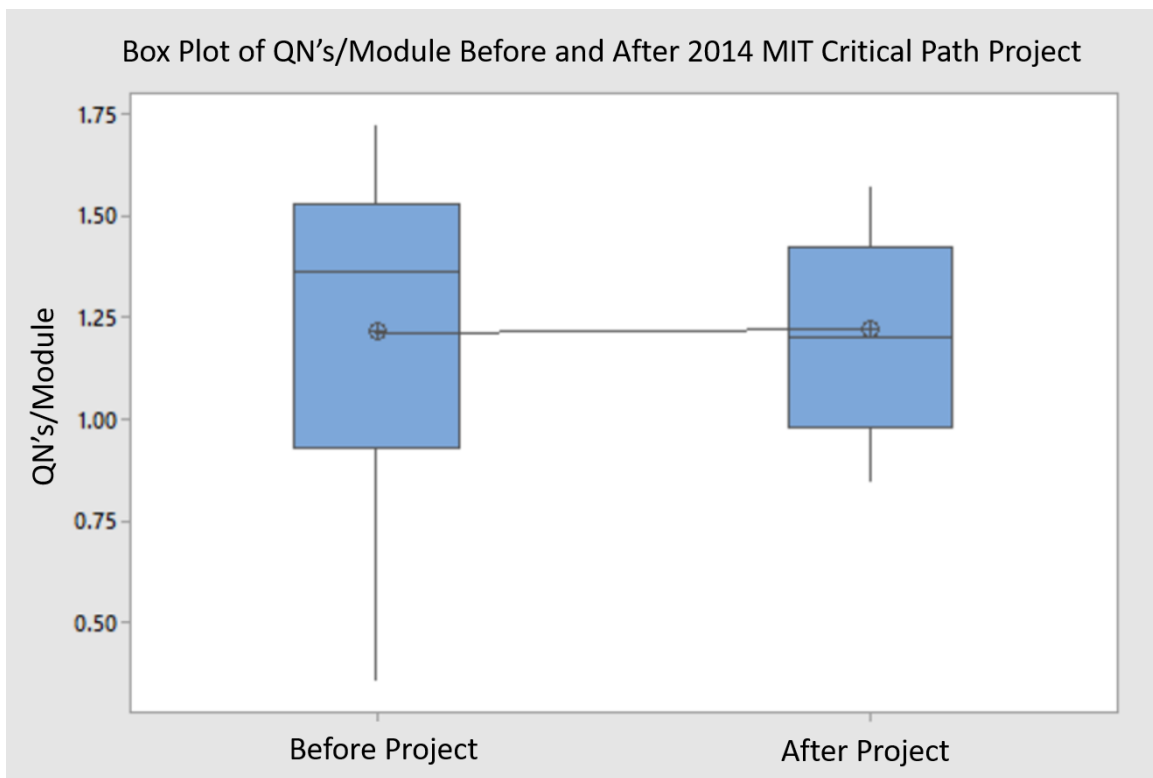


Figure 2-7: Monthly QN/module Distribution Before and After MIT UES Critical Path Project

area as a result of the impending changes coming to the assembly procedures as they are made digital by the implementation of IOMS, an Applied Materials home grown step-by-step assembly instruction program. The time line for this software roll-out is within the next year. Many of the ambiguities and shortfalls of the current .pdf files are set to be addressed. For example, each assembly step will be recorded independently with materials consumed being recorded in sync with each assembly step.

2.4.2 Effect of Shortages on Quality

One area that was repeatedly mentioned by assemblers in conversation as an area of improvement when it comes to quality is the effect of shortages on the build sequence. Building out of sequence has the potential to affect quality as the standard operating procedures are designed to be the best assembly path. The most egregious "critical" shortages require building out of sequence, assembling around a missing part, or adding complexity by having to assemble, disassemble, and re-assemble to meet both the delivery date and accommodate the missing part. The team used the crossdock information from the SAP MRP system to find historical accounts of shortages for the most recent year's worth of data. A crossdock is the term used when material is routed directly from the incoming shipment dock to the assembly line. The major reason this occurs is when a part is shorted and the demand is called for during a build. While this record does not capture whether the assemblers had to build around the missing part during assembly, this had to be acknowledged as a limitation to the data available for this analysis. Anand, Daigle and Ismail then paired the shop order or tool number order driving the crossdocked demand to the Quality Notification count for the tool number for a period of May 2015 - May 2016. The result was a plot of data points with the count of Quality Notifications logged against the tool as the dependent variable and the shortage occurrences as the input variable. This plot can be seen in figure 2-8. While the fit is admittedly weak, a 99% confidence band on the slope of the line was also included in the image to show that despite a poor fit to the data, a positive correlation between the input and output variables is statistically

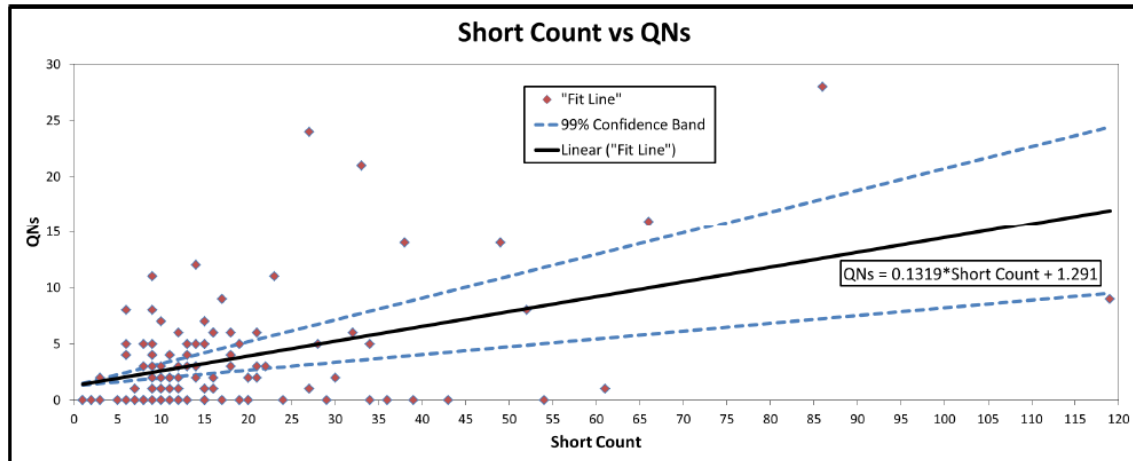


Figure 2-8: Scatter Plot of Part Shortages vs. QNs on a Tool for 2015-2016

very likely to exist.

While an exact causal statement such as 20 shortage occurrences leads to 5 QNs (for example) would be statistically inappropriate to make, the positive correlation between these two variables as indicated by the shortage count vs. QN count confidence band is still useful information. Due to the positive correlation between short occurrences and manufacturing QNs against a tool, shortage occurrence reduction was identified as an item for Anand, Daigle and Ismail to address as part of the quality improvement effort.

2.4.3 Data Shortcomings

From the manufacturing perspective, the conclusion drawn on the relationship between material shortages and quality is in agreement with traditional manufacturing principals. Following a standard build procedure and assembly step-specific kitting are proven methods for improving manufacturing quality in almost all settings.

Other statistical analysis performed by this Co-op team did not deliver as clear of results. These analyses included a look at Quality Notifications vs. the ratio of experienced worker hours put into the tool. For this analysis, all assemblers were classified as either experienced or inexperienced based on their time working for Applied Materials on their specific assembly area. A worker with under 6 months experience

working on a module was considered inexperienced. The ratio of inexperienced worker hours to total hours was plotted against the number of defects on the tool. The relationship was simply too confounded to observe a clear effect. The relationship was insignificant statistically using the data from the last year's worth (May 2014-May 2015) of tool builds. While reason suggests that inexperienced assemblers would likely make more errors than their experienced colleagues, the relationship was not statistically significant. However, it was findings such as this one that led Anand, Daigle and Ismail to believe that data accuracy was a greater issue than anticipated.

Examining individual variable's causal effects with a grouped output variable like the QN/module count is a weak approach as it is similar to running an experiment without isolating individual treatments from one another. Admittedly, it is an approach that will only show the inputs that are the strongest contributors to the defect count. However, running controlled builds (an experiment) to observe for a change in the defect rate when defects are in the range of about 1.0 defects per module build is also unrealistic due to time constraints and the effect on the production environment. Therefore, Anand has outlined several data collection recommendations in his thesis. For more discussion on specific measurable variables and their utility, please reference Anand's work [1].

Chapter 3

Critical Shortages Project

This chapter describes the steps taken to reduce the occurrence of material shortages that affect manufacturing quality as it relates to First Pass Yield. While rework due to material shortages is recorded as an individual category of rework for financial accounting purposes, as outlined in Chapter 2 of this paper, Anand, Daigle and Ismail have shown that there is an external effect of a material shortage on assembly quality that results in additional rework. This additional rework results from building around missing parts or assemblies that are shorted. It is this form of rework that the Critical Shortages project aims to reduce. The project was called Critical because of the hypothesis that missing certain parts during the assembly process resulted in higher rework rates; hence being deemed a Critical Shortage. It is also important to remember throughout this chapter that while the suggestions here follow many best practices in inventory management, this project is primarily motivated to improve manufacturing quality, not to necessarily manage the supply chain as lean as possible.

3.1 Current System and Procurement Types

3.1.1 2-Bin Kanban System

At Applied Materials Varian Division, material can come through the receiving docks through a variety of procurement methods. The following list of procurement types

are relevant to this project:

- Standard Purchase Order (PO) of COTS part
- Purchase Order of Varian-designed part (VO)
- 2-bin Kanban part order (KC)
- Large Kanban order (KB)

Purchase order (PO, VO) parts are ordered in advance of the machine build lay-down date by the MRP system at their published lead time. kanban (KC and KB) part types have negotiated lead times with the vendor. The vast majority have been promised at a 5-day lead time. The vendor carries sufficient stock of these items to have the part available at this reduced lead time. KB items are large frames, magnets or other large items that, while on a reduced lead time, are not stocked in any real quantity at Varian. They are delivered directly to the floor as they arrive from shipping just-in-time.

KC parts are much smaller, frequently used parts that can be ordered on a 2-bin kanban system. The current 2-bin system is designed with the intention that a bin holds enough inventory for two weeks worth of manufacturing and sales need. When one bin is depleted, an order is sent to the supplier for a full bin's worth of parts. The second bin is then used over the 5-day lead time and beyond, until the supply in that bin is exhausted. This cycle continues at steady state. The bins are re-sized at the start of each quarter using the new sales forecast of demand.

KC parts became of interest to Anand, Daigle and Ismail because of the frequency of KC procurement type shortages. It was discovered during the crossdock shortage analysis described in Chapter 2 that shortages of KC parts were high relative to the number of KC parts on a Trident Ion Implantation tool. Figure 3-1 shows the number of shortage occurrences of each procurement type beside the number of parts on a Trident tool of the same procurement type.

While KC is not the largest category of part types at Applied Materials, the KC part type category is comprised of many of the frequently used parts in Varian's

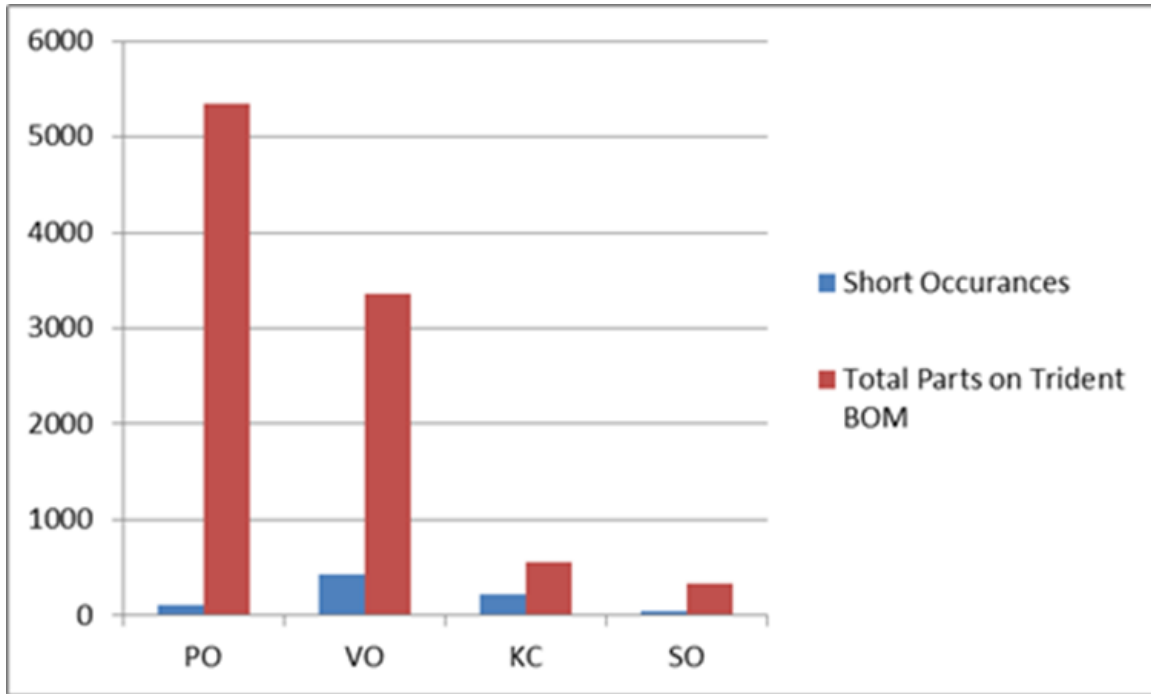


Figure 3-1: Shortage Counts Relative to Number of Parts on Tool

product line. The high ratio of shortages to total parts on the tool in the KC category was of concern, and was identified as a potential area of improvement. Anand, Daigle and Ismail began a detailed examination of the calculations used to size the two bins on this 2-bin kanban system for weekly demand. As it turns out, the calculations showed cause for concern.

To begin, the 2-bin kanban system limits the flexibility of the inventory management system as it does not offer additional benefits over a reorder point policy for holding inventory in the world of modern ERP. The 2-bin system would have been very simple if ordering had to take place via phone and there was a manual inventory count every day as in a historical manufacturing environment where ERP software was not readily available. The 2-bin system maintains the same push-pull boundary as a reorder point stock policy, as manufacturing pulls from an warehouse inventory of parts as needed, and Varian pulls from the supplier when the inventory reaches a set reorder point, which in this case is the size of one bin. Anand, Daigle and Ismail recommend a reorder point policy and recommend that the reorder point provide a 97% service level over the 5-day KC part lead time.

Before this project, sizing the bins starts when the inventory manager pulls a new forecast from the SAP ERP system for the next quarter. In this report is a lumped demand forecast driven from a handful of demand sources:

- Applied Global Services (AGS) sales demand
- Varian Division manufacturing demand
- Emergency Orders for customers with tools that are not operational

The demand forecast for each and every KC part is laid out on an Excel spreadsheet in calendar form for each business day of the 3-month quarter. Therefore, any statistical analysis is performed on a daily demand forecast. In the following equation, each of the two bins in the kanban is referred to as a *Pull*. In the existing formula, a Pull is calculated using the lead time for the part (LT), the weekly safety factor for the part (an effort to account for demand variability), the average of the daily demand (μ_{day}), and the standard deviation of the daily demand (σ_{day}). This calculation is shown in equation 3.1.

$$Pull = (LT \times WSF \times \mu_{day}) + \frac{1}{2}\sigma_{day} \quad (3.1)$$

This equation contains a mathematical error. In order to provide an accurate safety stock level, the standard deviation of daily demand must be corrected for the number of days over which the bin is designed to hold inventory. While the daily average consumption can simply be multiplied by 10 days for most parts (5-day $LT \times WSF$ of two weeks) to cover the average demand for two work weeks, the standard deviation must be multiplied by the $\sqrt{10}$ to scale the standard deviation of daily demand to a two week period. The corrected bin formula using the current methodology is shown in equation 3.2.

$$Pull = (LT \times WSF \times \mu_{day}) + \frac{\sqrt{10}}{2}\sigma_{day} \quad (3.2)$$

The $\frac{1}{2}\sigma$ term in equation 3.2 was designed with the intent to accommodate any variation in demand over the life of the bin for KC parts. Originally this number was

not $\frac{1}{2}\sigma$, but σ . Under pressure to cut inventory, the company had moved to smaller protection against unexpected variation. Additionally, the use of a weekly safety factor as another method of compensating for demand variation is unnecessary if the safety stock term is calculated correctly. It was realizations like these that created cause for shortage concerns for Anand, Daigle and Ismail.

3.1.2 Gold Square System

In addition to the material procurement methods described above, sub-assemblies produced in the Varian Supermarket are either built-to-order or built-to-stock, where the built-to-stock system is called the Gold Square system. The Gold Square system is a form of kanban system where there are a specified number of squares calculated for a particular part number and multiple demand sources, such as production and sales, pull directly from the stock of assemblies on the gold squares. The number of squares is therefore the stock level, and the reorder mechanism is a daily inventory count where the number of squares that are empty is recorded and new shop orders are cut to the supermarket to replenish the empty squares. As with the KC part types, the number of squares (stock level) is calculated quarterly based on the demand forecast. The equation used to calculate the number of squares is shown in equation 3.3.

$$\text{Number of Squares} = \mu_{week} + \sigma_{week} \quad (3.3)$$

While this equation is mathematically correct, it only provides a weekly safety stock of one standard deviation of the weekly demand. If demand were normally distributed, the service level would only be approximately 68%. This conclusion of the theoretical service level also created concern for Anand, Daigle and Ismail.

3.2 Demand Characterization and Curve Fitting

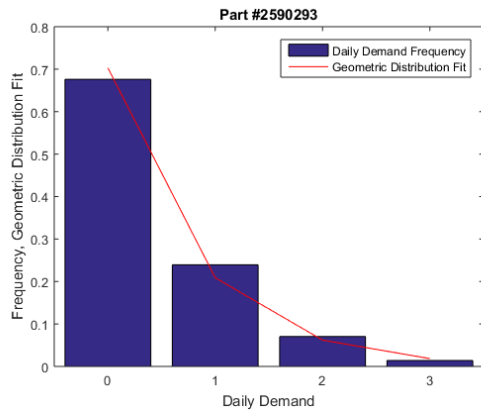
In subsection 3.1.1, the current bin method was shown to have had an error in the bin size calculation. However, this mathematical change was made irrelevant by

the realization that the internal daily demand for two-bin Kanban parts and Gold Square assemblies is in fact non-normal. The number of gold squares and the 2-bin kanban system bin sizes discussed in the previous section assume a normally distributed demand for individual parts and assemblies over the daily demand. In this case, the policy would require a roughly normal distribution of weekly demand for these KC and Gold Square items. In his work in Appendix C, Ismail questions the normally distributed demand assumption [2]. He plotted the forecast demand for each part number on the KC and Gold Square procurement types, and realized that the demand distributions were not normal in nature. In fact, the daily demand distribution for the vast majority of parts looks roughly exponential. However, as the plots show in figure 3-2, the demand histograms are not continuous like an exponential function, but discrete like a geometric distribution. Ismail checked this hypothesis by fitting geometric functions to the demand for each part through the full quarter. The geometric daily demand fits were quite strong for both Gold Square and Kanban parts. The quantitative effects of assuming normally distributed daily demand are discussed in section 3.3. Some example fits are shown in figure 3-2. For a detailed discussion of the forecast demand fitting process, refer to Ismail Appendix C [2].

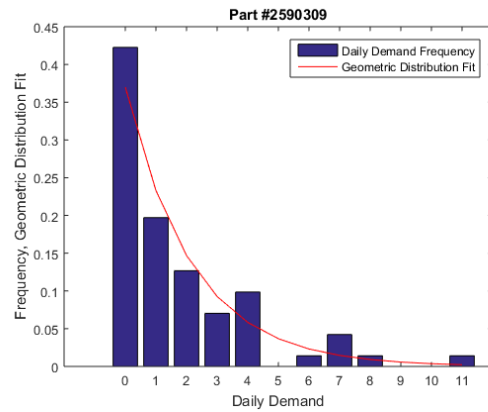
3.3 Reorder Point Selection Using Two Plausible Distributions

3.3.1 Theoretical Discussion

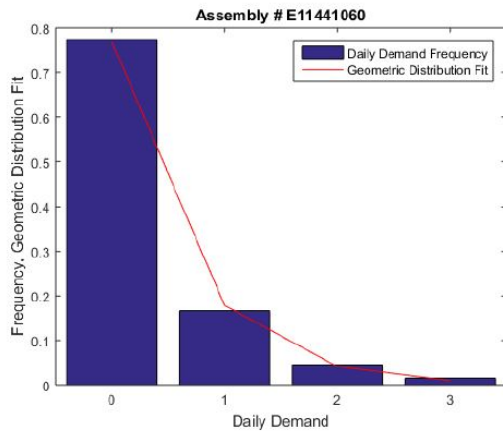
After establishing that forecast daily demand for KC and Gold Square parts are best approximated by an exponential distribution, Anand, Daigle and Ismail sought to apply this approximation in order to create an appropriate reorder level that satisfies a high service level over the replenishment lead time, which is five days for most parts. Finding a reorder point by directly using the fitted geometric distribution would be inappropriate as this would give the probability of satisfying all daily demand requests. The definition of service level established here is the ability to satisfy demand



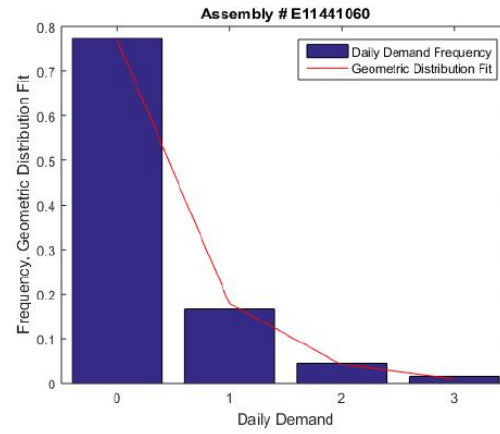
(a) Demand Fit for Example KC Part



(b) Demand Fit for Example KC Part



(c) Demand Fit for Example Gold Square Assembly



(d) Demand Fit for Example Gold Square Assembly

Figure 3-2: Example Geometric Daily Demand Fits

over the part replenishment lead time, which is usually negotiated with the supplier to be no more than five days. This definition means that the reorder point must be assigned such that repeated sampling from the geometric daily demand distribution on each day during the replenishment time does not cause a stock out. Repeated sampling from multiple geometric distributions can be aggregated together to form a single new distribution if the geometric distribution parameter, which is probability (p), is known from fitting the geometric distribution to each individual part number's daily demand. This combined distribution is called the negative binomial distribution [4]. In fact, the geometric distribution is a specific case of the negative binomial distribution where the number of successes, k is equal to 1.0. The negative binomial distribution is characterized by two parameters, the number of successes, k and the probability of success, p . As discussed above, the number of successes in this case is the number of geometric distributions to be sampled (5 due to the 5-day lead time). The discrete negative binomial probability distribution function can be written generally as a function of its two parameters. In equation 3.4, x is the number of trials on which the k th success occurs.

$$P_{NegBinom}(x; k, p) = \binom{k + x - 1}{x} p^k (1 - p)^x \quad (3.4)$$

The shape and rate parameters effects are best explained in figures 3-3 and 3-4. Notice the special case when $k = 1.0$, where the negative binomial distribution function simplifies to the geometric probability distribution with only the input parameter p . Higher values of k give uni-modal distributions that differ from the normal distribution.

In this context, the number of successes, k , is the number of geometric distributions being sampled from over the lead time. For most cases, this k -value will be 5.0 which corresponds to the 5-day lead time for the part. The probability parameter, p , corresponds to the fitted probability obtained from the daily demand distribution that is geometrically distributed. Recall from Appendix C of Ismail [2] that the geometric distribution fit parameter is the probability p . Probability (p) was found using

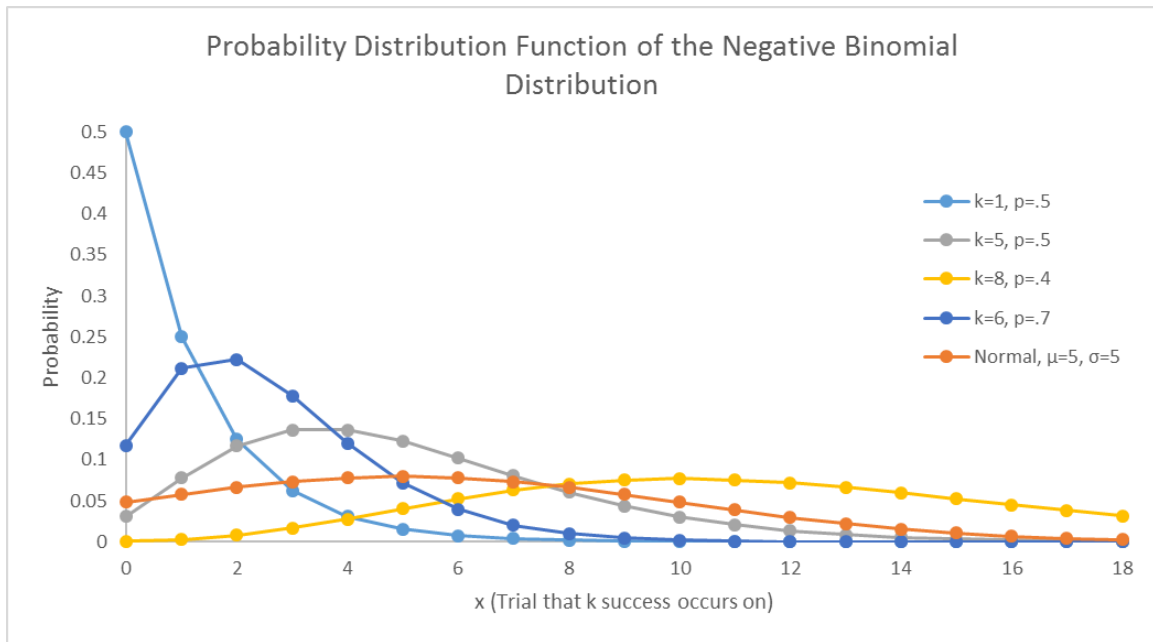


Figure 3-3: The Parameters of the Negative Binomial Distribution

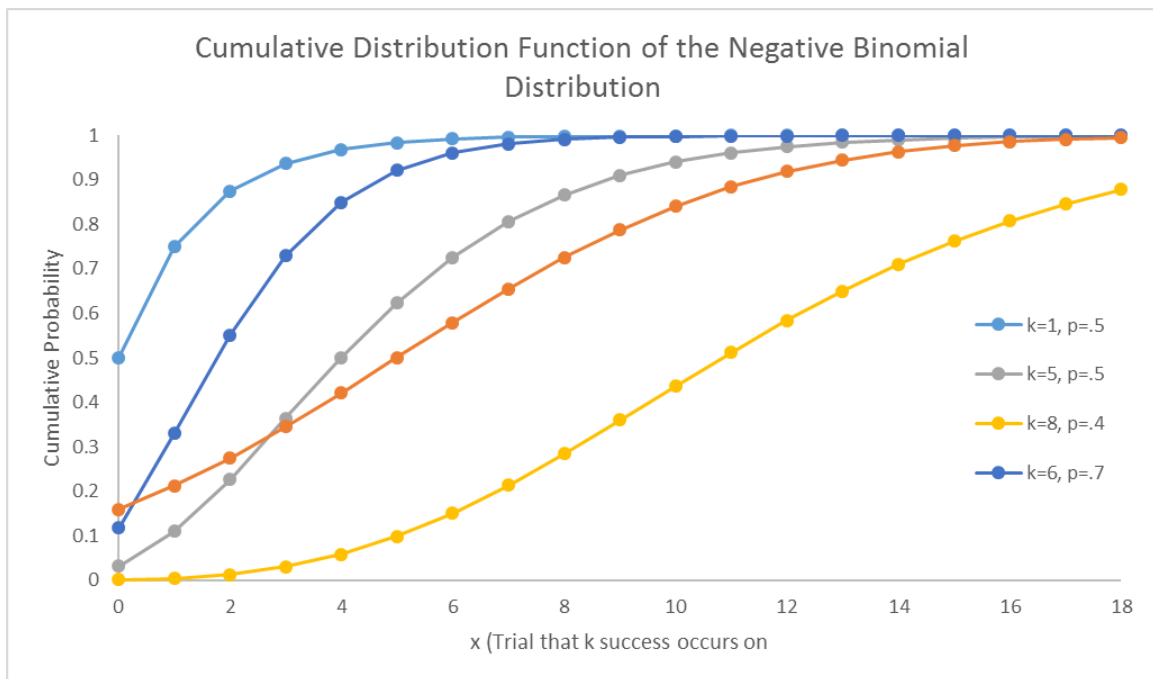


Figure 3-4: Negative Binomial Cumulative Distribution Function

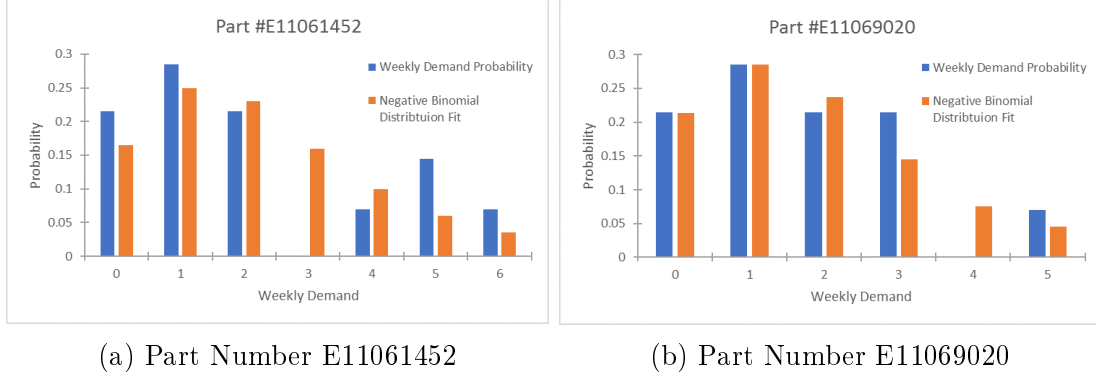


Figure 3-5: Example Weekly Demand Distributions and Model Verification

a MATLAB fitting function to the daily demand distribution.

To verify the fit of the model, the weekly demand forecasts were plotted for several part numbers in both the Gold Squares and KC part types to confirm the assumption that the 5-day demand was best approximated by the negative binomial distribution. Figure 3-5 shows the histogram plots of the weekly demands over the 3rd quarter for two example part numbers.

The plots serve as a check on the assumption that weekly demand is negative binomial-distributed. While some strongly negative binomial shaped distributions were observed for many part numbers, some more questionable plots were also observed. While the negative binomial distribution may be a good fit for the model, it does not appear to be drastically different than a weekly demand approximated by the normal distribution. Returning to figure 3-4, the normal distribution shown does not look significantly different from the negative binomial distribution above the 90th percentile. In inventory management, the 90th percentile for service level and above is the area of concern. Therefore, while these two distributions may be different, the effect on the inventory reorder point was found to be quite small. The effect on the reorder point is explained in detail in section 3.3.2. Given the strong geometric daily demand fits, and the relationship between the geometric distribution and negative binomial distribution, treating the weekly demand (or any multi-day demand) as negative binomial distributed may be plausible, but not significantly different than the normal distribution. As also discussed in Ismail Appendix C, the ease of use of

the normal distribution in Excel as opposed to fitting geometric parameters using MATLAB may be a benefit to those at Applied Materials. Were Applied Materials looking at sub 90% service levels, the use of the negative binomial distribution may be of more importance, however, this is not the case in this problem. The benefit of the ease of use of the normal distribution going forward seems to outweigh the minor improvement in demand fit using the negative binomial distribution, especially over the 90% service level mark.

3.3.2 Applying Inventory Methods

According to Simchi-Levi et al., a continuous review inventory management method typically provides more responsive inventory management than a periodic review method [5]. At Applied Materials Varian Division, the use of SAP MRP allows a continuous review inventory control method to be implemented. In a continuous review policy, whenever the inventory position falls below a certain reorder level, R , the system orders some quantity, Q units. The reorder point is made up of two components. The first is the product of the average daily demand (μ_{day}) and the lead time (L). This component ensures that the system has enough inventory to cover the expected demand over the lead time. The second component is the safety stock, which is the amount of inventory needed to cover the warehouse against deviations from the average daily demand over the lead time. The safety stock is calculated using the daily standard deviation (σ_{day}) scaled by the lead time (L) along with the z-score for the desired service level (Z). The reorder level is calculated using equation 3.5.

$$R = L \times \mu_{day} + z \times \sigma_{week} \times \sqrt{L} \quad (3.5)$$

One of the assumptions behind this equation is that the daily demand is random and follows a normal distribution [5]. As detailed in section 4.2, this assumption was a serious point of debate due to the close fit of the geometric distribution to daily demand, with weekly demand being plausibly better approximated by the negative

binomial distribution. Daigle and Ismail sought to compare the results of the two reorder points calculated for weekly demand using the normal and negative binomial distributions to officially conclude the analysis. The new formula sought to protect Varian against nearly all demand variation over the replenishment lead time for parts that fall under both the KC and Gold Square procurement systems. This scenario is solved by using the inverse of both distributions with their parameters as inputs in statistical software. Statistical software makes the use of the negative binomial distribution simple given an appropriate understanding of the software and an understanding of the components of the distribution itself. For example, the website Real Statistics Using Excel has a downloadable toolpack that that allows simple use of the negative binomial distribution inverse function directly in Excel [6]. The Excel equation requires only the desired service level, as well as number of successes, k , and probability, p , discussed in 3.3.1. The normal distribution function comes standard in Excel. Equation 3.6 and equation 3.7 show the Excel syntax with the downloadable RealStats toolpack. Equation 3.6 simply takes the parameters of the Negative Binomial distribution and takes the inverse CDF of the distribution to return the reorder point. Equation 3.7 uses the desired service level and essentially a normal distribution lookup table to return the z-score for the safety stock level.

$$\text{Reorder Point} = \text{NegBinom.Inv}(p, k, \text{Desired Service Level}) \quad (3.6)$$

$$ZScore_{\text{reorder point}} = \text{Norm.S.Inverse}(\text{Desired Service Level}) \quad (3.7)$$

The results of the comparison of reorder points using the negative binomial distribution and the reorder point obtained using the normal distribution were determined to be not significantly different. At the 97% service level, the difference between using the negative binomial distribution and the normal distribution for KC reorder point calculation was only about \$150,000 on well over \$7 Million worth of KC inventory. Due to the simplicity of understanding to outside users and those at Varian, the MIT team decided to recommend the use of the normal distribution for reorder point

calculation, while both models seem to be reasonable approximations of the weekly demand distribution at high service levels.

3.3.3 Recommendations and Results

Moving forward with sizing the reorder point for each part number using the normal distribution, the MIT team was able to calculate expected shortage reductions and cost increases incurred while holding more inventory at Applied Materials. A detailed presentation of this summary can be seen in Anand's thesis, Chapter 3 [1].

It is the recommendation of the MIT team that Applied materials follow a 97% service level for the reorder point for all KC part types. 97% was selected as it balanced inventory cost increase with a drastic reduction in expected shortages over the year. This service level change would result in a 35% increase in expected KC inventory compared to present stock levels. However, rework hours needed to install the shorted part will fall. Factoring in these costs, the total KC cost change would be an expected approximate increase of \$320,000, or a 19% increase. However, this increase would come with an approximately 80% reduction in the number of annual shortages of KC parts. As shown in Chapter 2, this 80% reduction would be helpful to increasing manufacturing First Pass Yield.

As for the inventory policy in the Supermarket for gold square assemblies, a 99% service level should be adopted as it ensures the least shortage occurrences for the important gold square sub-assemblies. However, based on the current lead time for Supermarket assemblies of approximately 6 days, the inventory required to protect Varian against variation in demand over the 6 day period would be an unreasonable increase. Each of these scenarios and a hypothetical scenario analysis can be seen in Anand's work [1]. The MIT team determined that it was best to advocate a parallel effort to reduce lead time in the Supermarket in order to reduce the replenishment time for gold square assemblies. The MIT team advocates reducing the Supermarket lead time to a 3 day period, which would help to minimize the cost increase of holding enough inventory to satisfy the 99% service level. This scenario would result in a \$130,000 increase in inventory costs (approximately 20%). However, Applied

Materials would be expected to see a 74% reduction in shortages from the gold square assemblies. This shortage reduction should have a positive impact on quality as gold square assemblies are likely to be critical sub-assemblies to the larger modules.

It should be noted that this reduction in shortages and overall recommendation is only possible with a parallel effort to reduce supermarket lead time. Without this effort, Applied Materials would be forced to hold much more inventory on the gold squares to adequately protect itself against demand variation during 6 days of demand, as this is the current state. Therefore, it is important to begin analyzing the effort required to reduce the lead time for gold square assemblies. The topic of lead time reduction will be continued in Chapter 4 of this Thesis.

Chapter 4

Supermarket Lead Time Reduction Project

This chapter describes the efforts taken to reduce the total lead time of assemblies produced in the Supermarket at Applied Materials Varian division. The total Supermarket lead time is defined as the time period from when the part is first ordered to delivery at the main module flow line. As discussed in chapter three of this thesis and detailed in Anand's work [1], the appropriate Gold Square inventory level is highly dependent on the required time to replenish an assembly placed on the Gold Square kanban system. In short, reducing lead time through the Supermarket allows Varian to hold less Gold Square inventory while still protecting itself against demand variability. Without a lead time reduction project, the MIT team would have been forced to recommend significantly increased inventory as the Supermarket lead time in the current state is running on average to be about five to six days.

4.1 Value Stream Mapping

At the time of this writing, inventory levels on the Gold Square kanban system were calculated to last through one week of average demand for each assembly number and add one standard deviation of the weekly demand for each assembly as safety stock. This calculation is detailed in Chapter 3, equation 3.3. One standard deviation

of protection against demand variation should provide about a 84% service level on weekly demand. In order to prevent the frequent shortages that would be experienced at this service level and improve manufacturing quality, the MIT team concluded that inventory levels must increase if the Supermarket lead time remained the same. However, increasing inventory levels on the Gold Square system is not possible in the present state. Varian would not be able to actually increase inventory levels due to the lack of labor capacity in the Supermarket assembly area. In fact, increasing inventory levels would create a surge in demand on the Supermarket, and simply put the Supermarket further behind. As opposed to presenting the previous finding that inventory levels needs to increase on the Gold Squares, the MIT team decided it was best if one group member joined an ongoing Supermarket Value Stream Mapping project. As discussions with Supermarket workers and supervisors revealed, the Gold Square kanban system was no longer being used as designed and was actually being used as a safety stock area as opposed to a kanban system. The ideal system for Applied Materials was unclear without further investigation of the nature of business in the Supermarket. This investigation took the form of the value stream mapping process.

4.1.1 Present and Future State Analysis

The value stream map is a powerful tool in the manufacturing engineer's toolbox. The value stream map (VSM for short) is a flowchart that chronicles the flow of information, material, people or other players in a manufacturing system with the purpose of eliminating unnecessary process steps or other forms of non value-added tasks henceforth referred to as waste. The VSM is set up to make forms of waste apparent to viewers, who are often employees of all organization levels as part of a Kaizen workshop. A Kaizen workshop is a gathering of employees of all levels and a complete break from work to analyze and improve the manufacturing or other relevant process. During a Kaizen workshop, supervisors encourage employees to place sticky notes on a large poster or projection of the current state value stream process map. These sticky notes include questions, comments, pain points or other recommended

improvements to the current process. In the absence of a Kaizen workshop, it falls on the value stream mapping team or individual in charge to capture the insights of the line workers on his or her map.

In his manual [7] "Product Development Value Stream Mapping," Dr. Hugh McManus writes that an individual should strap himself to the "product" when drawing out the relevant manufacturing process on a VSM. When lacking a physical part to ride on, McManus writes on page 38 that "you must strap yourself to the information—the work package that starts with the process inputs and accumulates and transforms until it becomes the process output [7]. His other recommendations include mapping "in pencil" to avoid wasting time on the map format, collecting information in person, and mapping the entire value stream to ensure that all those viewing the VSM will see the big picture [7].

While there are different variations on each VSM, there is some common formatting. On the VSM, tasks are represented with a rectangle, decisions are represented with a diamond, triangles represent a queue, thick arrows represent the main process flow, and thin arrows represent information flow. A castle-wall looking time line often runs along the bottom of the VSM, with downward steps in the line representing in-process (cycle) time and upward steps in the line representing wait time.

Once a present-state value stream map is created, it is reviewed for accuracy. When those involved with the VSM process are satisfied that the VSM is accurate, this version of the VSM is considered the current or present-state map. The VSM engineer, team, or group of stakeholders must then evaluate the value added tasks that make up the present state process. McManus writes on page 49: "Most of the tasks on your map will be necessary for completion of the overall process." However, the team must then "evaluate *how* [each task] adds value". Non-value-added tasks or problem areas are then identified with kaizen "bursts" [7]. Examples of information and physical waste include:

- Waiting
- Inventory

- Over or under-processing
- Unnecessary Movement
- Reformatting, reproduction, or re-entry of data
- Too much complexity within a process flow

Once the VSM team has identified the forms of waste present on the current state map, the team draws a future or ideal state map. The ideal state map draws the process in such a way that as many forms of waste as possible have been eliminated and the remaining process steps are critical to the creation of value.

4.1.2 The Varian Supermarket Current State Map

The Applied Materials Varian Division Supermarket current state map can be seen in figure 4-1. The current state map was drawn by a manufacturing engineer at Applied Materials in pencil by physically walking the process. Buy-in was created with workers by speaking with employees of all levels, and approval that this VSM in fact represented the current state of affairs was given by the Manufacturing Director.

Several forms of waste were identified on the current state value stream map. The following list identifies the most important problem areas:

- A 30 hour delay between the use of a Gold Square assembly and the point when a new shop order is cut to replenish the item
- 564 assemblies waiting to be cut as shop orders
- 26 shop orders waiting in a pre-review queue
- A wasteful process step that included 37 shop orders in a queue awaiting final prioritization
- 45 shop orders cut and awaiting kitting
- 20 picked kits awaiting a technician to build the assembly

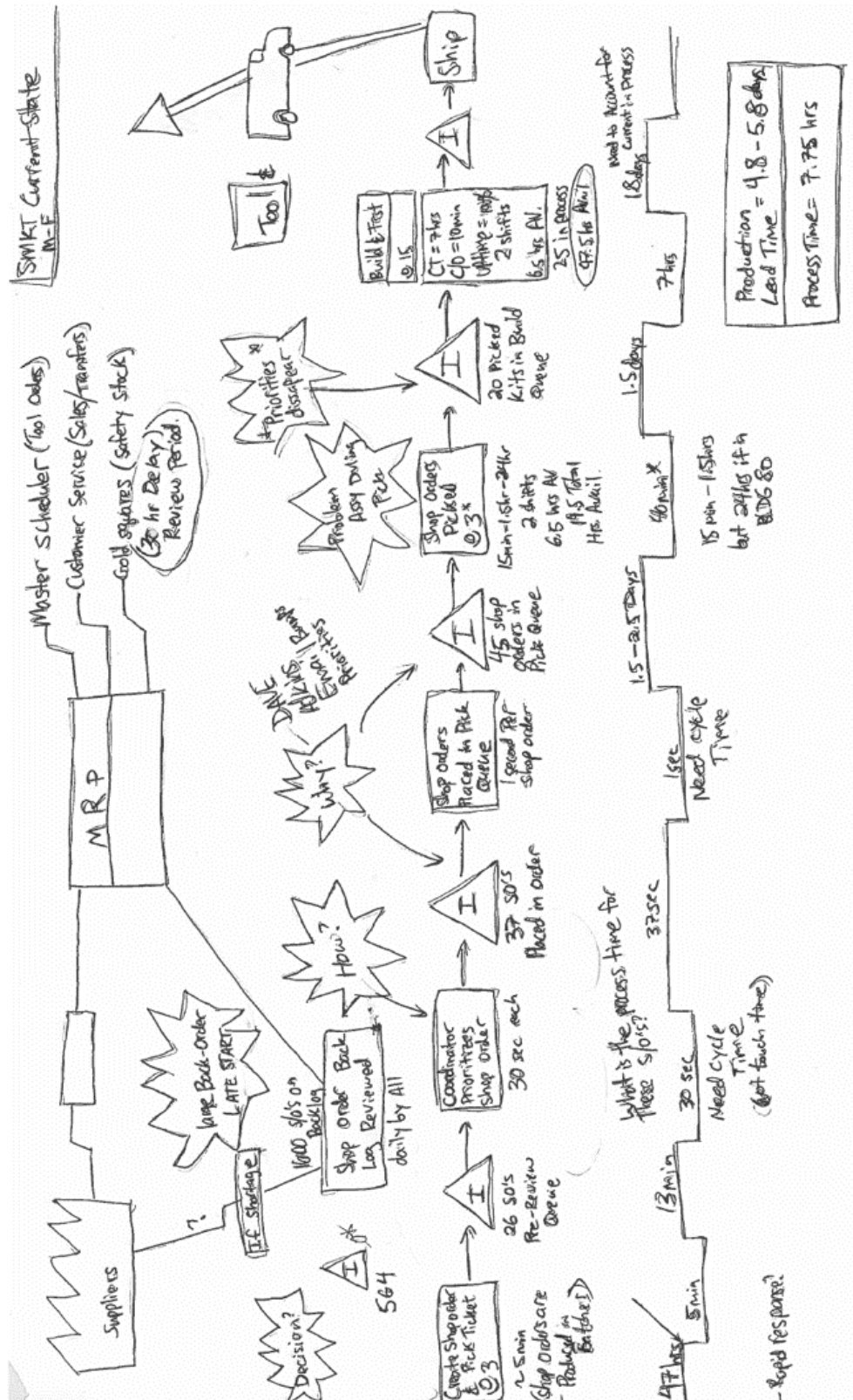


Figure 4-1: Current State Supermarket Value Stream Map

This VSM shows that in the current state, the Supermarket experiences a production lead time of about 4.8-5.8 days. On average however, an assembly will only experience about 7.75 process hours. This is often the discovery found when analyzing process maps. Most of the time it takes to make a Supermarket sub-assembly is lost in the form of waiting or queue time. While sometimes unavoidable, waiting and queue time is almost always regarded as waste. It is therefore the goal of the Value Stream Map team to eliminate or reduce the lengthy wait time experienced by Supermarket assemblies while in the shop order form before physical fabrication of the assembly.

4.1.3 Supermarket Ideal State Value Stream Map

The ideal state process map was drawn after the VSM team agreed on the wastes drawn on the current state process map. The ideal state map can be seen in figure 4-2.

In the Supermarket ideal state map, all of the queues that added additional days of lead time to the Supermarket assemblies have been eliminated. Orders are collected in the MRP system (SAP) and shop orders are cut when they are added to the daily schedule. Gold Square assemblies are added directly to the daily schedule as well. In an ideal state, the shop order prioritization is first-in-first-out (FIFO).

After drawing the future state map, it is up to the project leader to identify the individual projects that are needed to take the organization from the current state to the future state. The team identified that Varian must address (1) the 30 hour review period for Gold Square replenishment, (2) the capacity constraint based on the number of workers available to perform Supermarket work, (3) the 24 hour pick time for parts that come from the supplemental warehouse located external to the supermarket, and (4) ultimately address whether there will be any prioritization between assembly orders that originate as a sales order versus a machine production order in the daily schedule. This thesis will delve into the capacity constraint problem presented by the VSM.

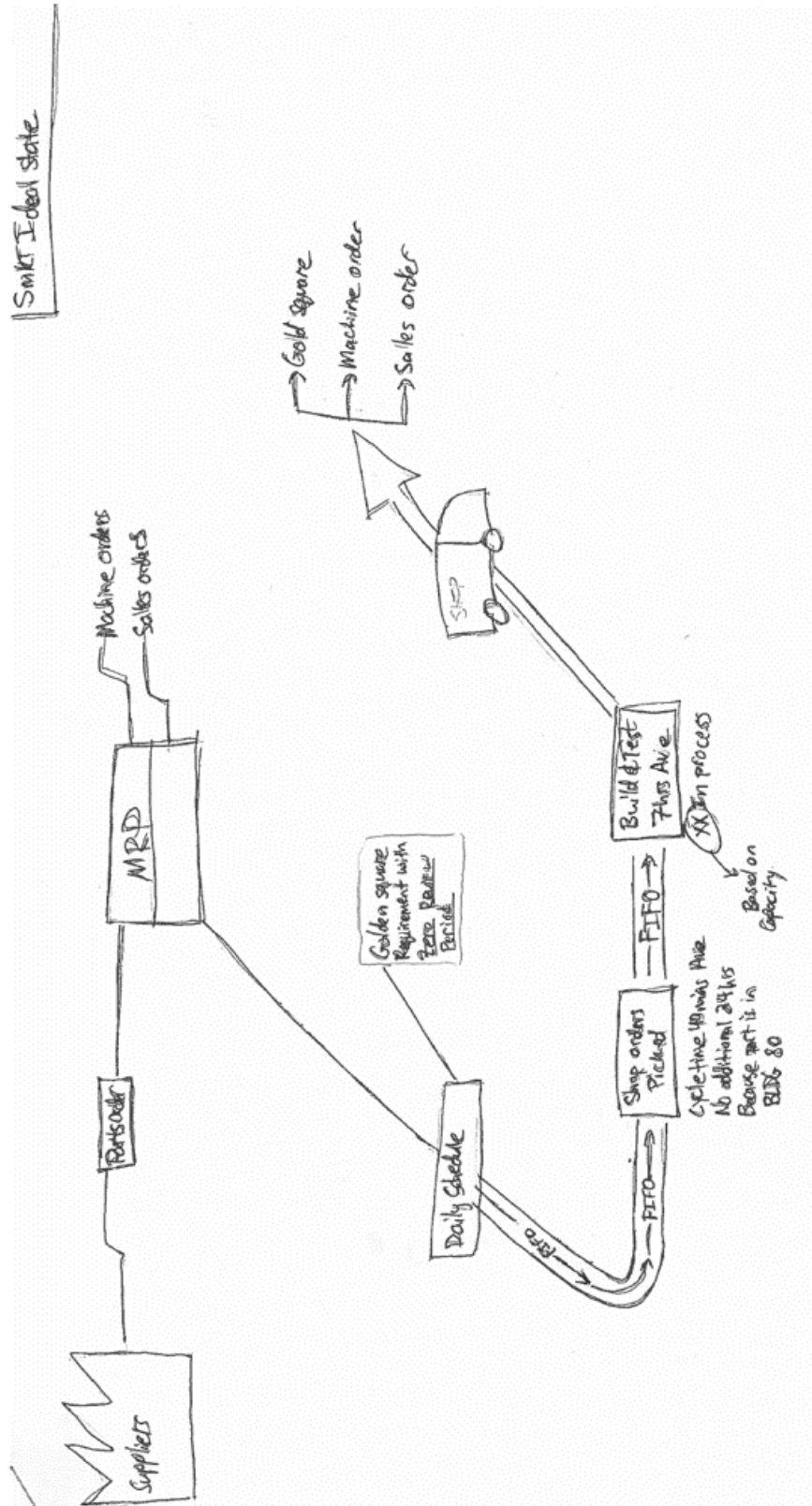


Figure 4-2: Ideal State Supermarket Value Stream Map

4.2 Capacity Constraint Analysis

The approximately 4-5 day backlog of assemblies awaiting to be built by the Supermarket was largely caused by capacity issues within the Supermarket. As the Supermarket builds many varieties of hand-made assemblies, capacity refers to the number of workers present to build Supermarket assemblies during each shift. At the time the present state value stream map was drawn, there were approximately 8 workers on each of the three shifts that worked in the Supermarket. The Supermarket shift structure is as follows: The first shift is an 8-hour day shift that works 5 days (Monday-Friday) per week. The second shift is a 8-hour evening shift that works 5 days per week (Monday-Friday). The third shift is a 12-hour weekend shift that works 3 days per week. Each worker on third shift works both weekend days and is scheduled for one other weekday shift for 12 hours to total 36 total hours worked per week. The number of workers on each shift was chosen based on a simple calculation that took the SAP sales forecast and multiplied by the number of in-process hours to be built over the quarter. The total hours were divided by the worker hours available and workers were added or dropped from a shift to balance the gross number of hours. While some more realistic adjustment factors were used such as worker productivity (factored in at 85 percent), the calculation did not incorporate the effects of random shop order arrivals, or the effects of mandatory employee training before building certain Supermarket assemblies. The ballpark calculation used previous to this analysis can be seen in equation 4.1.

$$\text{Number of Workers} = \frac{\sum \text{Forecast Shop Order Hours}}{\text{Shift Hours} \times \text{Days Working} \times \% \text{ Efficiency}} \quad (4.1)$$

Such a ballpark calculation without considering these more complex effects created large queuing times as these effects placed the Supermarket near its maximum capacity. At the start of this analysis, the primary concern was the effects of a worker not being able to build the required assembly as he/she was not trained to build what is called a certified assembly. However, it became clear during the analysis that the

major concern should have been the increase in capacity needed to absorb variation in the production forecast.

4.2.1 Goals and Methodology

While lead time reduction was the primary goal of this analysis, the secondary goals included inventory optimization of the Gold Square finished assemblies and an accurate labor force size to respond quickly to demand. In order to model the many complex effects of the Supermarket system, a MATLAB simulation was written. Simulations of complex systems, while not exact, offer the ability to manipulate many variables and observe the combined effects. This model takes the following information as inputs:

- Current Shift Structure
- Number of hours worked during each shift
- Number of workers on each shift
- List of assemblies each worker is certified to build
- Production forecast for the quarter

The input forecast is of the format shown in the excerpt of table 4.1. While this table is only an excerpt, the Supermarket builds hundreds of assemblies that are individually numbered and each is assigned a standard number of build hours. Table 4.1 also extends right to accommodate the forecasted demand for each day in the quarter.

Assembly Number	Standard Build Hours	# Needed Day 1 of Qtr.	# Needed Day 2 of Qtr
2056897	5 hrs	0 units	1 units
3518754	2 hrs	2 units	0 units
6578914	12 hrs	1 units	3 units

Table 4.1: Production Forecast Format

As for the input of worker certifications, the MATLAB program loads each worker as an individual vector of table entries in the format of the table excerpt shown in

table 4.2. The complete table includes enough columns to store worker certifications as binary on/off values for all of the possible Supermarket assemblies.

Worker	Shift	Assembly 1	Assembly 2
Worker 1	1	1	0
Worker 2	2	0	1
Worker 3	1	1	1

Table 4.2: Supermarket Certifications Matrix

The simulation itself initializes a day and loads the daily schedule off the production forecast. The simulation then loads the workers for shift 1 and takes discrete time steps through the shift assigning assemblies to available workers. Specifically, the code simulates the following sequence of physical events:

1. All shop orders for the day are cut and assumed to be picked
2. Shop orders that require certified (specially trained) assemblers are placed on top of the list of shop orders
3. All workers arrive at the start of the shift and are assigned work one by one
 - (a) The program checks whether the first worker is trained for the first shop order
 - (b) If yes, this worker begins work
 - (c) If no, the next worker steps up to see if he is certified to complete the shop order
 - (d) If none of the workers on this shift are trained to complete this shop order, the program attempts to assign the next shop order to the group of workers
 - (e) Work is assigned in this way until all workers are busy
4. As time progresses, workers complete jobs and are re-assigned to a new job until their shift is up
5. Work in progress after a shift changeover is prioritized first to be assigned to new workers on the next shift

6. The work order assignment process for all subsequent shifts follows the same process as the first shift until the day is complete, at which point the program loads the next day's work
7. Any remaining work from the previous day is prioritized in the following day in the order below:
 - (a) All remaining work in process from yesterday
 - (b) All remaining shop orders from yesterday
 - (c) Today's certified assemblies
 - (d) Today's general assemblies
8. The program steps through each day of the quarter in this way

The program tracks several important metrics. It first plots the backlog summary, which is a day-by-day account of the cumulative remaining work to be done at the end of each day. After quite a few runs of the simulation were completed, and the the model converged towards an appropriate number of workers per shift, the backlog summary still showed that a backlog of work is simply unavoidable due the the variation in daily demand. In fact, the coefficient of variation of the total daily build hours from the sales forecast is approximately 1.0. With such variation in daily production demand, some days the Supermarket will fall behind and others it will catch up. An example of the backlog summary produced by the simulation can be seen below in figure 4-3. On the horizontal axis is the day of quarter, and on the vertical axis is the number of total hours needed to build all the assemblies in the queue.

A short discussion should be made here of the significance of this plot. Simply put, a production system with variable demand requires either A) an appropriately sized finished goods inventory stockpile or B) excess capacity to account for fluctuation in daily demand. Of course, these are competing cost interests. In the case of Applied Materials Varian division, the Manufacturing division is held responsible for personnel and staffing, while the Supply Chain division is held responsible for inventory management. Such an organization structure makes it difficult to balance the

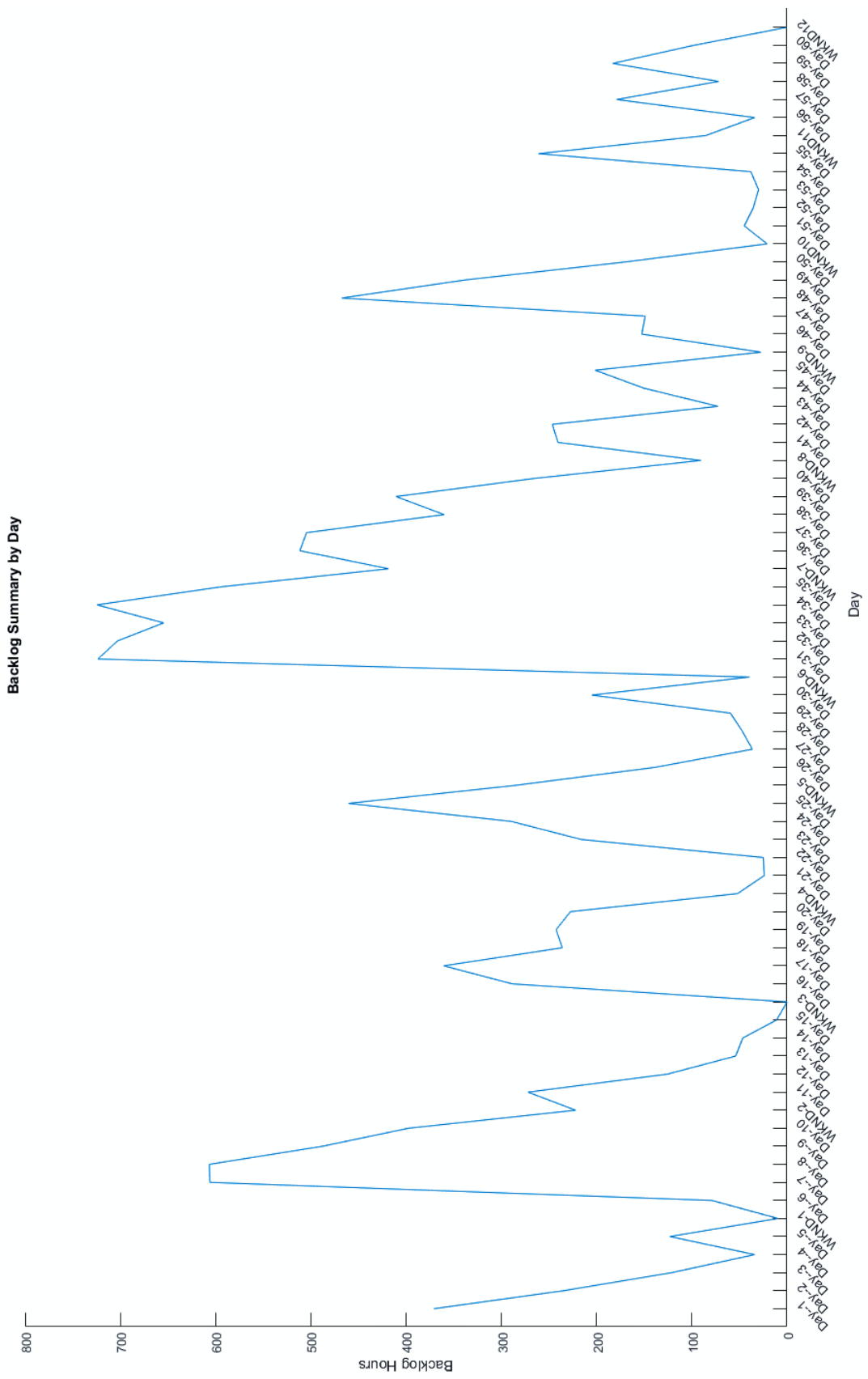


Figure 4-3: Backlog Summary with Recommended Workforce Structure

competing interests of finished goods inventory and capacity. Inventory, as discussed in Chapter 4, has a real and calculable holding cost. Likewise, hiring extra personnel to handle days with high demand for Supermarket assemblies is also a significant cost and could lead to idle capacity during days with low demand. As with many systems, these competing interests must be balanced.

The second output the program produces is called the simulation summary. The simulation summary is a graphical view of the average queue times for each of the different certified assemblies compared to the average queue time for all certified assemblies and the average queue time for all non-certified (general) assemblies. The simulation summary from the final run of the program and with the recommended number of employees and certifications can be seen in figure 4-4.

The program also prints a summary of each assembly produced and the queue hours to an Excel file. A limitation to this program is that it does not optimize itself. The program only gives the user the information needed to make decisions on whether to add/drop employees and do more or less employee training for each specific assembly. However, a little logic added to the output Excel file proved helpful when deciding whether to add or drop employees and certifications. The spreadsheet summed the total assembly hours on the production forecast for the day and then compared the queue hours for the certified assemblies to the amount of workload the supermarket experienced while the assembly was being built. Before this logic was introduced, it was hard to distinguish the cause of long queue times for a specific assembly. The assembly may have experienced long queue times on average due to a lack of trained workers to build that assembly or it may have experienced long queue times simply because the assembly was always ordered on a day when the Supermarket was especially busy. Specifically, the spreadsheet indicated that more certifications for the assembly should be added if on average the assembly number queued for greater than 5 hours more than the overall average for certified assemblies, and the assembly was requested on days with less than average workload. The spreadsheet recommends the user decrease the number of certifications for a specific assembly if the assembly queued for more than 3.5 hours less than the average certified assembly

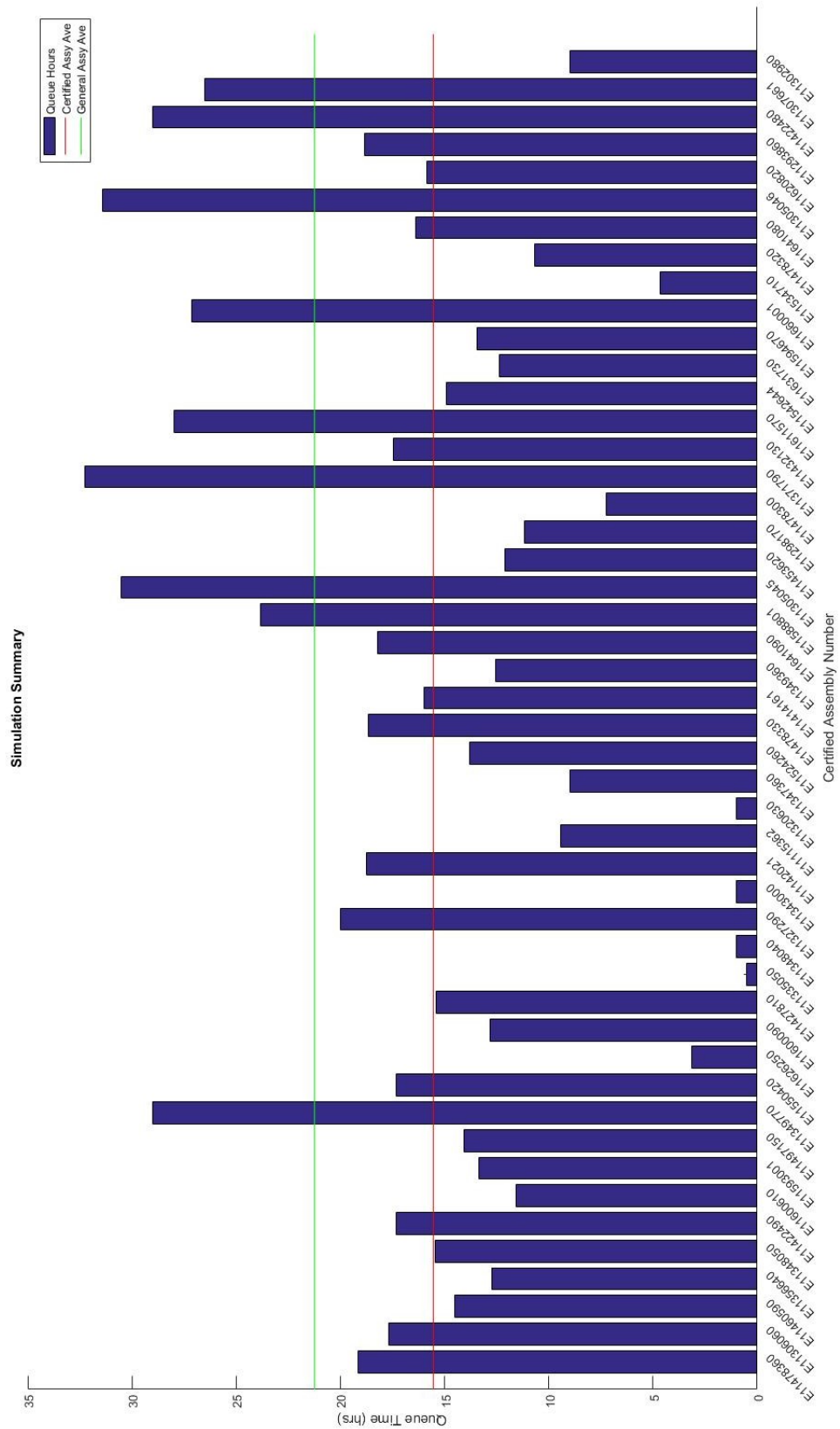


Figure 4-4: Simulation Summary with Recommended Workforce Structure

and the assembly was normally requested on days with more than average workload. Whether the assembly was requested on days with more or less than average workload was determined by comparing the average workload for a day across the whole period to the workload on days which that particular assembly was requested.

Over the process of several runs of the program, it became clear that prioritizing the certified assemblies over the general assemblies had the effect of the certified assemblies being completed several hours before the general assemblies on average. The results from the final run of the program can be seen in table 4.3.

	Certified Assembly (hrs)	General Assembly (hrs)	Overall (hrs)
Average	15.5	21.2	20.0
Std. Dev.	8.2	10.0	9.8

Table 4.3: Queue Time Summary

The prioritization of certified assemblies is important, however, because late general assemblies can be compensated for with overtime work. Often times the necessary certified assembler is not available to work overtime, but if all remaining assemblies are general assemblies at the start of the overtime period, this issue is avoided. Additionally, relatively few certifications are needed when the system prioritizes certified work, placing less burden on the system in terms of worker training.

Another notable conclusion was that spreading certified assemblers evenly across the three shifts led to the system requiring far fewer certified assemblers. Balancing the certifications across the labor force will prove difficult to implement, yet necessary if queue time reduction is truly desired. The recommended number of certifications by assembly, per shift can be seen in figure 4-5.

Perhaps the most expensive part of this analysis is the recommended increase in the size of the workforce. The recommended workforce size can be seen in figure 4-6. Of course this workforce size increase could be partially handled with a flexible workforce that allowed idle capacity on the main module assembly line to work on Supermarket assemblies during idle time, and vice versa.

Assembly	Current	Recommended	Change	1st Shift	2nd Shift	3rd Shift
EPM Lens	9	4	-5	2	1	1
Scan	4	4	0	2	1	1
Roplat	8	5	-3	2	2	1
Crion Roplat	3	3	0	1	1	1
Cartridge	8	4	-4	2	1	1
Tilter	3	2	-1	1	1	0
R&P Profiler	8	8	0	4	2	2
In Vac Profiler	8	3	-5	1	1	1
RMS (Rotary mass slit assembly)	7	5	-2	2	2	1
Elevators	14	9	-5	5	2	2
PFG	19	4	-15	2	1	1
Pre-Cool	3	4	1	2	1	1
Process CIM	3	7	4	4	2	1
Source Chamber	12	6	-6	3	2	1
Resolving Chamber	13	4	-9	2	1	1
XPVPS	9	4	-5	1	2	1
Resolving Assy	16	3	-13	1	1	1
Q2/Q3	13	4	-9	2	1	1
Manipulator	4	2	-2	1	1	0
EPM Chamber	12	5	-7	2	2	1
Ion Source	2	3	1	1	1	1
Total	178	93	-85	43	29	21

Figure 4-5: Recommended Certifications by Assembly, Per Shift

	Current	Future
1st Shift	8	14
2nd Shift	8	10
3rd Shift	6	11
Total	22	35

Figure 4-6: Recommended Workforce Size

4.2.2 Summary

As discussed earlier, demand variation creates a need for either increased capacity to handle high points in demand, or a finished goods inventory to do the same. In order to best balance the competing interests, this analysis was completed. The result is that for a make-to-order system with limited finished goods inventory available on the Gold Square Kanban system discussed in Chapter 3, the workforce size in the Supermarket must be increased. While queuing effects due to required training of the workforce to build certain assemblies were observed during simulation, these effects can be combated through the prioritization of certified assemblies in the build queue. The increase in the labor force size in the sub assembly area of about 50% over all three shifts can also be partially addressed by using idle capacity from the main module assembly line for general (non-certified) Supermarket assemblies during demand surges, as no specific training for these assemblies is required. Despite a large recommended increase in human capacity to build sub-assemblies, following this recommendation would result in the average lead time for Supermarket sub-assemblies being reduced from about 5-6 days to about 1.8 days. Very infrequently would the lead time for an individual assembly be over the 3 day threshold established in Chapter 3. This lead time reduction would enable lower Gold Square inventory levels and possibly a further shift towards a make-to-order system for Supermarket assemblies.

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Chapter 5

Model Based Engineering Project at the MIT Lincoln Lab

As outlined in Chapter 1, the MIT Lincoln Laboratory is a federally funded research and development center that applies advanced technology to problems of national security. The structure of the Lincoln Lab is as follows: There are 8 technical divisions that focus on specific areas such as Missile Defense, Air Traffic Control, Cyber and Information Security, Communications, General Engineering, General Advanced Technology, Space System and ISR/Tactical Systems. Within the General Engineering Division, there are 8 groups that deal with many fields of engineering from Systems Engineering to Optical and Control Engineering. Of specific interest to this paper is Group 71 – Mechanical Engineering and Group 72 – Fabrication Engineering. It is important to note that while Group 71 may have projects of its own, it is often tasked to be the hardware developer for other groups within one of the many other Lab divisions. Group 72 is the primary fabrication resource for Group 71 and other groups throughout the lab.

While complex systems are manufactured at Lincoln like in industry, the culture is one of innovation and research, which has left relatively little focus on manufacturing process improvement and general efficiency. Extensive process improvement and a manufacturing focus is a characteristic of competitive industry, but has been largely unnecessary in a research setting. At Lincoln, such improvement endeavors

have simply never been regarded as necessary to improving the quality of the research taking place at the Lab. However, under present fiscal restraint within the Department of Defense and the Department of Energy - major funding sources to the MIT Lincoln Lab - the landscape has changed: program budgets are shrinking, and design cycles have continued to grow shorter. Engineers demand more transparency to the fabrication process and desire quick turn-around times as well as exceptional quality for precision engineering.

5.1 Future State: The Model Based Enterprise

Despite relatively little focus in the area, the Lincoln Lab has long desired business process improvement to facilitate easier purchasing, fabrication, and assembly services from Group 72 – Fabrication Engineering. As previously mentioned, the integration between Group 71 and Group 72 is critical to the physical creation of the advanced research and development systems designed and tested at the Lab, and eventually deployed to the field. However, at this point in time, the processes by which the design and fabrication group integrate and work together to field a design are regarded as guidelines, and the standard practices that are followed are paperwork-heavy and cumbersome.

This is the environment that the Model Based Enterprise/Engineering (MBE) project at Lincoln Lab strives to change in the near future. According to the National Institute of Standards and Technology (NIST): “the core MBE tenet is that data is created once and directly reused by all data customers” [8]. Model Based Engineering aims to have data creators like CAD users and manufacturing plan developers create data only one time for use throughout the organization and across the fabrication shop floor. Previously, the philosophy was such that the CAD model gave way to written process plans, engineering drawings, and printed bills of material. In essence, the source of truth varied based upon who was involved with the manufacturing process at that time. A purchaser may view the bill of material as the source of truth of the product, while a machinist would only reference the engineering drawing as his source

of truth. However, both of these documents were replicated from information that existed or could have existed as part of the CAD model and its structure, yet was recreated because the model lacked complete definition for downstream manufacturing activities. An excerpt from the NIST MBE Summit can be seen below:

A model is a representation, or idealization of the structure, behavior, operation, or other characteristics of a real-world system ... A model is used to convey design information, simulate real world behavior, or specify a process. Engineers use models to convey product definition or otherwise define a product's form, fit and function ... In the context of manufacturing, model data drives production and quality processes. A product model used in manufacturing is a container not only of the nominal geometry, but also of any additional information needed for production and support. This additional data, known as Product Manufacturing Information (PMI), may include geometric dimensions and tolerances (GDT), material specifications, component lists, process specifications, and inspection requirements [8].

In today's software landscape, one of the most common methods to implement a Model Based Enterprise is to invest in Product Life cycle Management (PLM) software. This software allows structured data needed throughout the procurement and manufacturing process to be integrated into the product structure with the CAD model. This will be the approach Lincoln takes to achieve MBE changes. These database-like systems allow the automated production of supplemental manufacturing information driven from existing data in the CAD model. For example, using a Commercial Off The Shelf (COTS) item from the CAD library updates a bill of material, purchasing information, and assembly information from the information stored on the item within the database. Furthermore, this information exists as part of the complete CAD model and its integrated data, which means that users do not have to replicate information at later steps.

5.1.1 Relevant Requirements

The future state of the Model Based Enterprise at MIT Lincoln Laboratory is only enabled by a total effort between designers and fabricators. The program team tasked at Lincoln Lab to enable this change came up with many requirements of the future state of business at the Lab. However, as this project is limited in scope and time, this paper deals with specifically manufacturing scheduling and transparency goals. Of the many requirements of the future state, this project begins the preparatory work to achieve the following requirements:

1. Manage the manufacturing schedule
 - (a) Track deliverables against the manufacturing schedule
 - (b) Allow the schedule to be visible to all users across the organization
2. Pre-define fabrication routing and record all movement of assemblies through manufacturing and test
3. Shop capacity plan based on upcoming work
 - (a) Inform delivery dates based on available capacity and upcoming work
 - (b) Improve the accuracy of delivery date quotes
 - (c) Provide a simple way to request fabrication quote
4. Make procurement information available across the enterprise, including:
 - (a) Due Date
 - (b) Delivery Status
 - (c) Location in Building
 - (d) Lead time broken down by procurement/fabrication step

In order to enable the vision of the Model Based Enterprise, the manufacturing shops must feed data back to the engineers on manufacturing status and provide accurate quoting of fabrication times to upstream users. As a means to meeting

many of the project requirements, a software package called JobPack was tested. JobPack is a graphical manufacturing scheduling software specifically designed for Job Shops. The Lab had invested in JobPack in 2013, but despite the investment and considerable interest from leadership, the effort fell apart during implementation, and the software license was allowed to expire. Chapter 6 discusses the revival of this software as a means to accomplishing some of these Model Based Engineering project requirements in an out-of-the-box package.

5.1.2 Production Environment and Scope

Lincoln Lab has many advanced manufacturing technologies and many highly capable shops under the management of Group 72. The Lincoln shops include:

- Machine Shop
- Sheet Metal
- Welding
- Electronic Fabrication (PC Boards)
- Clean Room Services
- Mechanical and Electronic Assembly
- Environmental Test

Due to the limited timeline of this project, this paper only addresses methods, changes, and improvements in the area of the machine shop. However, even scoping to only the machine shop is no small endeavor. The shop has 12 full-time employees and one supervisor, and handles fabrication requests for a large mix of systems. When it comes to shop organization, the Lincoln Laboratory machine shop is set up much like a typical job shop. Some characteristics of a job shop are outlined as follows:

A job shop is a type of manufacturing process in which small batches of a variety of custom products are made. In the job shop process flow,

most of the products produced require a unique set-up and sequencing of process steps. Job shops are usually businesses that perform custom parts manufacturing for other businesses. In the job shop, similar equipment or functions are grouped together, such as all drill presses in one area and grinding machines in another in a process layout. The layout is designed to minimize material handling, cost, and work in process inventories. Job shops use general purpose equipment rather than specialty, dedicated product-specific equipment [9].

When a job arrives to Group 72, it is planned out and given what is called a routing. This route includes the list of steps that must take place before completion. Therefore the routing includes tasks and machine functional groups within the Lincoln Lab machine shop. Routes are required to be processed in a specified order. In a custom, low volume manufacturing setting like that of the job shop, each job may require many different steps, all of which are defined on the route. During quoting, the job is assigned an expected processing time to complete each step on the route. This time includes the setup of the machinery, fabrication of any custom fixtures and the actual cutting or printing time for subtractive and additive processes.

Scheduling the jobs through a job shop when there is finite capacity in terms of machines and staff has always been a difficult task. In fact, it is a form of optimization problem where there are many jobs, machines, and personnel. The optimization problem is made more complex due to added business constraints. For example, certain jobs are for more important customers and take priority over other jobs.

As solving such an optimization problem is difficult and less than practical in a production environment without software, traditional job shop scheduling was done with heuristics. There are numerous job shop scheduling heuristics. These heuristics are simple rules such as scheduling all jobs by the closest due date or scheduling the shortest duration jobs first at each workstation. Other, slightly more complex rules exist such as the least slack rule, where jobs are scheduled such that jobs with the least time between the deadline and the processing time completion date (slack) are scheduled first. At present, Lincoln Lab uses none of these techniques, but the shop

supervisor dispatches jobs to in the order he believes best to meet all completion dates.

With the computational power of JobPack, the software is able to optimize the schedule based, according to the developer, on: 1) meeting as many due dates as possible and 2) keeping machines as highly utilized as possible. While the developer would not give any more details on the exact specifics of the optimization process, the important takeaway is that the software analyzes the many routes and schedules jobs to ensure completion of as many jobs as possible by the due date. A secondary goal of this work will be to assess the strengths and weaknesses of the JobPack software, and whether it looks like the software could help increase the on-time completion performance of the Lincoln Lab machine shop. The setup, analysis and evaluation of the JobPack software will be continued in Chapter 6.

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Chapter 6

Lincoln Lab Shop Scheduling and Capacity Planning

In order to meet the desired outcomes cited in Chapter 5 in the area of manufacturing scheduling and planning, an approach that combines the use of the JobPack scheduler and additional data analysis was tested. While the Model Based Enterprise goals related to schedule visibility and transparency are largely addressed by the out-of-the-box JobPack software, improving the quoting accuracy and doing so in a simple manner requires further thought.

6.1 Proposed Methodology for Improving Delivery Quote Accuracy

While meeting the quoted due date is dependent upon the shop performance, it is also dependent upon the accuracy and feasibility of the quote itself. JobPack claims that its software can help with optimizing a production schedule to meet more completion dates. It also seems like it could be used to quote new jobs with a more accurate completion date than the present method. However, JobPack is a scheduler software. It does not forecast future complications or take into account random events that cause schedules to slip. Using the JobPack software and quoting completion dates

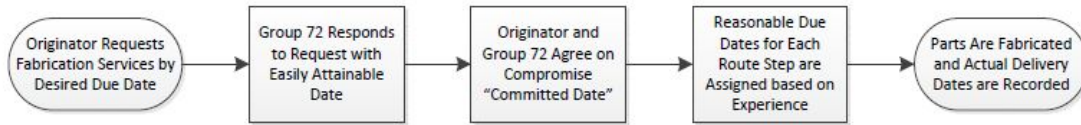


Figure 6-1: Current Completion Date Quoting Process

based on a perfect schedule would be a recipe for failure. There will always be sources of error and delay in a manufacturing environment that cause rigid schedules to slip. Any quoting method must have a means for dealing with these delays.

6.1.1 The Current Quoting Process

Currently at the MIT Lincoln Lab, the completion date quoting process follows the steps outlined in figure 6-1. The committed date is for all practical purposes, the deadline that the shop holds itself to.

The current quoting process and shop setup yields approximately a 75% percent on time percentage for the committed date. This percentage is the cumulative on-time percentage across all the shops on the route. The difficulty with this measurement is that if there are multiple shops on the route, each shop must meet its individual deadline a high percentage of time in order to see a high on-time performance of the committed date. Take a three shop route for example: The part must be machined, precision cleaned, and inspected. If all three of these shops had a 90% on-time percentage, the overall on-time delivery rate for this three shop route would be 72.9%. Therefore, a high individual shop on-time rate is critical to overall on-time performance. The current on-time percentage for the machine shop is approximately 80% percent.

The current quoting process, while based on the experience of long-time employees, is not scientific. It is the belief of this author that a new process could better predict completion dates by collecting data on the sources of delays that cause schedules to slip. While it is the goal of manufacturing philosophies such as Lean to remove sources of variation that cause random events, a good quoting process should also

predict the occurrence of these events to better inform the true delivery date.

6.1.2 General Quoting Ideology

The logic behind this problem approach is as follows: By gathering data on the sources of schedule slip, Group 72 could find some sort of *predictive indicator* to inform its delivery quotes of how much the JobPack schedule might slip by the time the part is completed. In the absence of a period of time to collect data on the performance of the Lincoln shops while using JobPack, simulating these sources of random events was the method used to find a predictor variable of schedule slip. The simulation performed here creates phantom jobs in the JobPack schedule that only exist to mirror random events that may take place during the real life manufacturing process. With accurate data on the nature of the random events that cause schedule slip, a reasonable simulation of completion times could be created that identifies an anticipated schedule slip time – henceforth referred to as the Shop Loading Buffer – to add to real life jobs. A future delivery date quoting process would add this Shop Loading Buffer to the scheduled delivery date.

6.2 Data Collection

For this analysis, data was collected on four sources of schedule delay. The sources of delay examined are as follows:

- Process time quoting error
- Walk-in fabrication requests
- Personnel illness (unforeseen absences)
- Machine failures

While there are undoubtedly other sources of schedule slip, the data available to analyze the sources of slip was scarce, and therefore the scope was limited to these four sources in the interest of time.

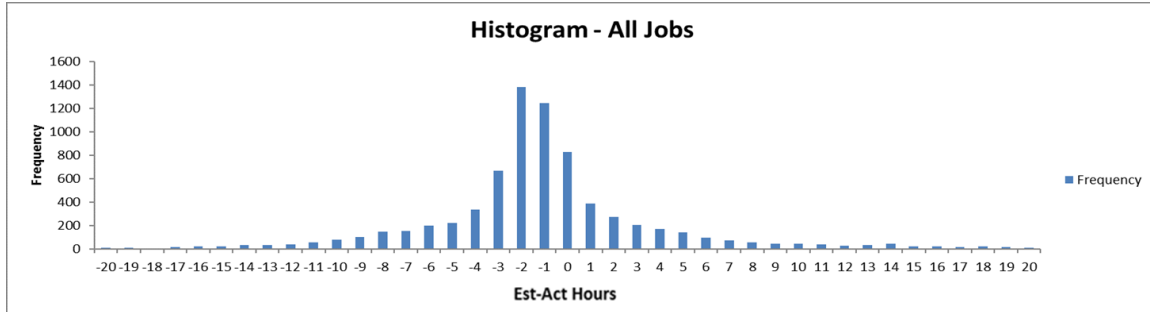


Figure 6-2: Process Time Estimate Error 2014 - Present

The first source of delay considered was the Manufacturing process time quoting error. This is the prediction error that occurs when the shop plans to spend 30 minutes on setup and 5 minutes of cutting time for 6 parts for a total of one hour of process time, but the whole process instead takes 1.5 hours. The error in this example (estimated time - actual time), is -0.5 hours. To gather historical data on this error, a fabrication engineer in Group 72 ran a SAP report to come up with the processing time error for all machining jobs from January 2014 to September 2016. The histogram of this error can be seen in figure 6-2.

The mean of this distribution is at approximately -0.98 hours, meaning that, historically, the Lab planners under-quote process times for machining jobs by on average about 1 hour. From speaking with shop supervisors, it is more likely that shop employees know the process time quote before starting a job and work at a pace such that they nearly miss the process time quote. However, there is a healthy distribution to this source of error. The tails of the distribution are quite large, meaning that some jobs are under or over-quoted by up to 20 or more hours. This distribution, while uni-modal, is not normal. The center is higher and the tails are longer than a normal distribution. To generate random events that mimic the raw data better than the normal distribution for simulation purposes, jobs were split into two groups. Jobs whose process time was greater than 6 hours were split from jobs whose process time was quoted at under 6 hours. The historical data showed that jobs quoted at under 6 hours of process time had a mean error of -0.6 hours and a standard deviation of 2.6 hours of error. Jobs with process time quotes of greater than 6 hours had a

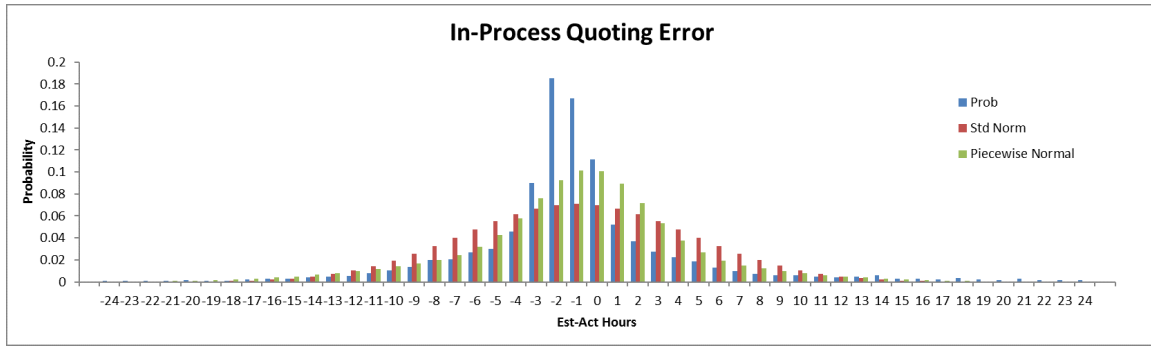


Figure 6-3: Process Time Error Distributions

mean error of of -1.5 hours and a standard deviation of 7.3 hours. During simulation, random error to processing time was generated from these two distributions. To check that splitting these two distributions off from one another resulted in a combined distribution that looked more like the raw data, the two distributions were combined, normalized (divide each probability by 2 because there are two distributions being combined and the total cumulative probability must still be 100%) and plotted on the same axis. The piecewise normal (for lack of a better term) distribution does perform better than a standard normal distribution. The mean of the piece wise normal distribution was -1.02 hours with a standard deviation of 5.49 hours. These descriptive statistics show that the composite distribution preserves the mean shift and standard deviation of the raw data, and better captures the peak value than a normal distribution fitted to the raw data. This result can be seen in figure 6-3. While the piecewise normal distribution is not perfectly accurate and further data manipulation could likely produce a better distribution to represent the raw data, it was thought that this product was adequate for simulation purposes.

The second source of delay studied here were walk-in orders to the machine shop. A few years back, Group 72 stopped giving a designation to walk-in orders in SAP, therefore, data was not readily available in this area. In order to create a realistic estimate of the amount of walk-in work that the machine shop experiences, the methods found in Douglas W. Hubbard's book "How to Measure Anything" were used [10]. Hubbard's book stresses that the absence of easily manipulable data does not mean that there is not any data available for analysis. While incomplete, the data

available can often times reduce uncertainty enough to make better decisions. One technique that Hubbard presents is the use of educated guesses made by “calibrated” individuals. An individual is calibrated through practice at estimating. Additionally, it is important to ask questions in such a way that the person answering the question can arrive at a confidence interval range for the true value of the metric of interest. For example, while an individual may not know the exact amount of money in his or her wallet, they could likely give you a possible range. Hubbard would pose this question as follows: “What would you bet is the *most* possible amount of money in your wallet?” You could then pose the question the same way for the least amount of money. According to Hubbard, this range actually corresponds quite nicely to an interval estimate of the true value - say a 90% confidence interval for example. The benefit of this technique is that different individuals carry vastly different amounts of money on them. For example, one person may have a range of \$5 to \$60. Another may never leave home with less than \$50 to \$200. The expert, who in this case is the owner of the wallet, is the only person who could give this range. While it would be wildly inaccurate to take a guess at a value like those in this example without asking for a co-worker’s wallet, a calibrated estimator can give much better data resolution than the examiner had before, without the calibrated range estimate. Examples aside, the point of this discussion is that by using this method, a researcher does in fact know more about the metric of concern; potentially enough to make a better business decision.

In this study, the calibrated estimate technique was used with the machine shop supervisor to come up with the number of walk-in orders in a week during normal operations. His response was a calibrated range of 1 to 6 walk-in orders. A normal distribution was assumed to lie within this range, meaning the mean of the number of walk-in orders per week was estimated to be 3.5 with a standard deviation 0.83 walk-ins. A random number generator was used to create random events in frequencies in accordance with this distribution.

This study also gathered data on the capacity loss due to personnel falling ill. Group 72 had financial data in this area to make this part of the analysis simple.

The data given showed that the probability of an employee taking a sick day was 5%. A random number generator was used to generate sick day events for simulation purposes. A random number from zero to one was generated for each employee for each day of the simulation period, and a phantom job titled “Personnel Sick” was created if the random number was less than or equal to 0.05. The simulated job was then given a deadline of the date of the sick day event. This simulated job could then be added to the JobPack schedule.

The last form of random event modeled in this simulation was the delay to jobs caused by unforeseen machine failures. Unfortunately, the available data in this area was extremely sparse. In fact, it was discovered that the Lincoln Lab does not keep a comprehensive record of machine services and repairs. One employee, a machine service technician, began recording the machine services he performed in the various shops upon coming into the Lab from industry. The technician seemed willing to begin logging these services more religiously, however, the data available at this point was too sparse to be used for analysis purposes. The technician only had comprehensive service logs for the two 5-axis CNC mills. These maintenance logs were used to create a discrete time model to generate machine failure events for simulation. The maintenance logs contained the number of failures as well as the machine run time since machine installation. This information could be used to calculate the Mean Time To Failure using equation 6.1.

$$MTTF = \frac{\text{Run Time}}{\text{of Failure Events}} \quad (6.1)$$

The Mean Time To Repair a machine was calculated by taking the average of all repair times from the service logs for each machine. The probability of failure or repair at a time step was calculated using equations 6.2 and 6.3.

$$P(Failure) = \frac{\text{Time Step}}{MTTF} \quad (6.2)$$

$$P(Repair) = \frac{\text{Time Step}}{MTTR} \quad (6.3)$$

In order to generate random events, 1/2 day time intervals were used to step through the date range for the jobs loaded into JobPack. At each discrete time step, the two 5-axis milling machines could move from an up state to a down state and vice versa. A random number was generated for each machine at each time step, and if the random number fell below the probability of failure (or repair depending upon the machine state at the previous time step) the machine changed state from operational to out-of-service. The lengths and dates of the simulated failure events were recorded for each simulation run and loaded into the schedule as jobs.

6.3 Simulation and Data Analysis

Before simulating, the open order report from SAP as of November 11, 2016 was loaded into JobPack. The open order report is the list of incoming and in-process jobs to the machine shop. The predicted completion dates of all the jobs were taken as the output after running the JobPack schedule optimization algorithm. These completion dates were considered the optimal completion dates for all the jobs.

The new schedule, with the additional simulated phantom jobs added as representative random events seen by the Lincoln Lab machine shop that could cause schedule slip, was then loaded into JobPack. On each run of the JobPack scheduler, the random delay events were re-generated and loaded into the schedule. The completion dates for the real jobs in the open order report were recorded on each run of the JobPack scheduler. The delay time for each real job for each run of the scheduler was taken as the output variable. Recall from section 6.2 that the goal of this analysis was to find an indicator that would predict the schedule slip seen for an incoming job during its fabrication time. The following input variables were plotted against the delay time output value:

- Slack in Routing (Slack = Deadline - Remaining Processing Time)
- Total Time Scheduled to be Spent in the Machine Shop
- Total Processing Time

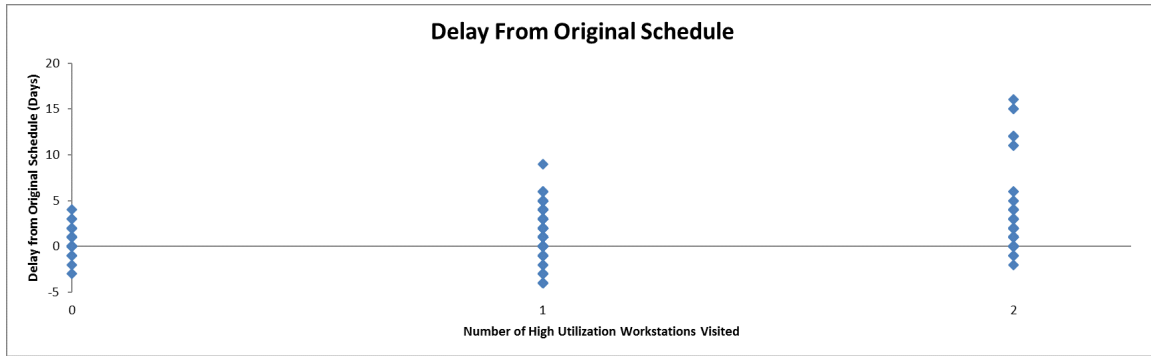


Figure 6-4: Highly Utilized Workstations Visited vs. Delay From Optimal Schedule

- Number of Highly Utilized Workstations Visited Within the Route

Little to no correlation could be observed between the first three items on this list. The number of highly utilized workstations on the route, however, did prove to be a suitable and simple indicator of anticipated schedule slip. A machine was considered highly utilized if it experienced less than 15% idle time in the next two week period with simulation data. A major limitation here lies in the setup for the JobPack software. Without purchasing the additional Personnel Package, the setup required the general machining work (work not going to 5-axis mills, EDM machines, etc) to be scheduled from one general pool. The result is that this general work is all considered highly utilized, when in reality, utilization might be below 85% for some conventional machining processes. The purchase of this package will be a recommendation made later in this chapter. The number of highly utilized workstations in the route for each job was plotted against the output of delay from the optimal schedule. The raw data plot can be seen in figure 6-4.

Figure 6-4 appears to show three different groupings based on the number of workstations visited. Based on this figure, it looks like the mean delay from the optimal schedule shifts upward and the spread of the delay increases as the part routing includes more highly utilized workstations. In order to test this conclusion, an ANOVA analysis was run on each of the groups (0, 1, 2 high-utilization workstations). As it turns out, the three groups are statistically different to 95%. This result means that it is highly unlikely that these groups come from the same population. Therefore,

different estimates of the three group means and spreads are appropriate.

Figure 6-5 shows each group plotted with the 95% confidence interval estimate of the mean of the group in red, and the 80% prediction interval plotted in purple. A prediction interval is an interval in which the next data point recorded should fall a certain proportion of time. The prediction interval equation is shown in equation 6.4. In this equation, \bar{X} is the sample mean of the group, S is the sample standard deviation, t is the statistic from the student's t distribution, n is the number of data points in the group, and α is the significance level desired for the range.

$$P(lower, upper) = \bar{X} - t_{(\frac{\alpha}{2}, n-1)} S \sqrt{1 + \frac{1}{n}}, \bar{X} + t_{(\frac{\alpha}{2}, n-1)} S \sqrt{1 + \frac{1}{n}} \quad (6.4)$$

Figure 6-5 shows an 80% prediction interval. Therefore, 80% of the time, a single new job would fall in this range. This information is useful because it means that 90% of the time, a new job that Group 72 is quoting would experience a schedule slip of less than the upper end of this range.

The distribution of the data in these groups is significant, as called out in the inlaid histogram in figure 6-5. The purpose of this call out is to show the shape of the distribution of the data. While the data is not normally distributed, the data is uni-modal and a prediction interval range is appropriate. The number of data points in each group is included in the figure because both the confidence interval of the mean and the prediction interval is influenced by this value. The most important part of figure 6-5 is the upper bound of the prediction interval. The actual numeric values of the mean of the interval and the upper bound can be seen in table 6.1:

High Utilization Mach. in Route	Expected Delay	90% Upper Prediction Bound
Zero	0.6	2.1
One	1	3.5
Two	2.5	7.1

*Note: All data is in time units of days

Table 6.1: Results: Upper Bound of Shop Capacity Buffer Estimates

It is likely that there will be apprehension to adding up to 7.1 days of Shop Capacity Buffer to a two high-utilization machine routing at MIT Lincoln Lab. It

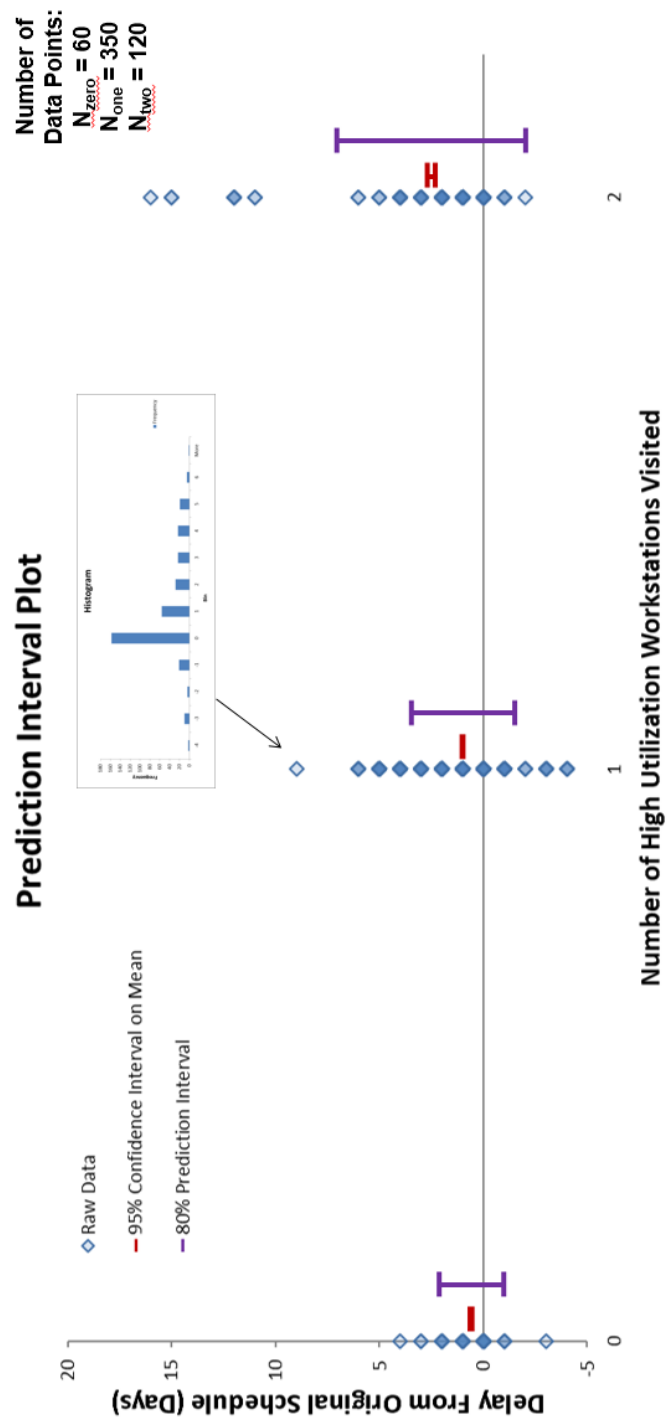


Figure 6-5: Anticipated Delay Prediction Interval Plot

is important to remember that this analysis is not recommending the addition 7.1 days of Buffer to the current quoting process (which includes some buffer time within each route step), but to a new quoting process that is based on the earliest delivery date available within JobPack. It is also appropriate to note that this information is based on one round of simulation data. The best long-term solution to assigning Shop Capacity Buffer would be to collect real time data on jobs while using the JobPack software going forward. This data collection approach would also help revise the Shop Capacity Buffer as more shops are added to the JobPack scheduler in addition to the machine shop. The Shop Capacity Buffer could be constantly updated to reflect new operating conditions by using a memory length to the data point measured. In this case, memory means that after a certain period of time, say one year, the data point used to calculate Shop Capacity Buffer is removed from the calculation.

The most important part of this analysis is demonstrating the link between highly utilized machines and potential for recurring delay due to random events. The recommendation here marks a key change in philosophy: Instead of effectively masking delay due to random events by giving each shop a buffer time at each step in the route, it is better to assign a scientifically calculated buffer time to the route as a whole, and assign work to machines using a capacity scheduling software.

6.4 Process Change and Recommendations

A new delivery date quoting process is needed to use the method presented in section 6.3. This process is the recommended list of steps taken upon receipt of a call to Group 72 for a fabrication request. Terms in bold are newly defined terms that will be explained.

1. Originator calls with **Desired Completion Date**
2. Planner creates process time estimates and enters hypothetical job into JobPack
3. JobPack revises schedule to include new job and best meet the Desired Completion Date

- (a) Planner checks whether any other jobs already in JobPack have been pushed past their **Network Finish Date**
 - i. If YES, Planner enters date one day later than the current Desired Completion Date. Return to step 3(a)
 - ii. If NO, proceed to step 4
- 4. The earliest Desired Completion date that does not impact other jobs becomes the Network Finish Date
- 5. Planner offers the Network Finish Date PLUS the **Shop Loading Buffer** to the Originator. The offered date becomes the **Commit Date**.
 - (a) Originator decides whether to accept the Commit Date
 - i. If YES, proceed to step 6
 - ii. If NO, the Originator takes the work out of house. Note that part of the route can be taken out of house if one only one step is over capacity.
- 6. Planner creates Network Order. The Network Finish Date is entered into SAP/JobPack to be viewed in the shop. The Commit Date is displayed to the Originator in PLM.

There are several terms that must be defined: The Desired Completion Date is the desired date with which the originator calls the Planner. If capacity is available, this date will be met. If not, other jobs will not be bumped back past their Network Finish Dates to meet this new request. The Network Finish Date is the date that the Machine Shop and all Group 72 employees work towards for a delivery date. The Shop Loading Buffer is the statistically calculated delay time over the original delivery date calculated upon network order dispatch. Finally, the Commit Date is the date given to the Originator as a latest delivery date. While they may see a tentative delivery date sooner than the Commit Date in any JobPack-created schedule, they are quoted the Commit Date for a latest delivery date.

6.4.1 Conclusions

This process aims to use JobPack's route processing capability during quoting. It also uses supplemental data analysis to revise the quote to take care of any predicted schedule slip. A major change between the old process and this recommended process is that the Originator of the fabrication request does not know the Network Finish Date. Likewise, the Group 72 employees do not know the Commit Date. Such a process sets up an incentive structure that will encourage fast completion while also encouraging realistic delivery date expectations with the Originator. The outcome of this recommendation would be a policy change that encourages ongoing statistical analysis of schedule slip and aims to improve delivery date accuracy. Additionally, were a statistically calculated Shop Loading Buffer to be added to completion date quotes, the on-time completion rate could be brought up to 90-95% from the current rate of 75% by simply adding the appropriate confidence level Shop Loading Buffer.

There are several other recommendations of note to be made moving forward at the Lab. In the area of data recording, Group 72 should begin recording data on machine failures. This data could be used for further simulation of random events and Lean efforts to reduce failures that can cause delays are based on machine reliability data. The Lab should also make a new effort to truly characterize the frequency and duration of walk-in orders. Walk-ins will always be a practice at the lab because there will always need to be last minute, mid-test fixes in a research environment. If this practice will always exist, it is important to plan appropriately and build appropriate capacity. Finally, as stated in section 6.3, the simulation done in this analysis should be superseded by recording real data on the relationship between high utilization machines and the potential for JobPack schedule slip.

Chapter 7

Summary and Conclusions

As stated in the opening chapter, this thesis is a compilation of two industry projects carried out by the Master's candidate at two separate locations. This thesis presents the analysis and summary of these projects with a detailed presentation of the significant findings and contributions. These projects were carried out at 1) the Varian Division manufacturing facility run by Applied Materials, Inc. (Nasdaq: AMAT) located in Gloucester, MA, and 2) the fabrication shop run by the MIT Lincoln Laboratory in Lexington, MA. Summaries of the findings of each project can be found in sections 7.1 for conclusions regarding the Applied Materials projects and 7.2 for conclusions regarding the MIT Lincoln Lab project.

7.1 Applied Materials Varian Division

The work carried out at Applied Materials Varian Division was performed as part of the First Pass Yield initiative within the company. The First Pass Yield (FPY) program is one of the major continuous quality improvement projects within the organization. First Pass Yield, as described in Chapter 2, is the proportion of fully operational wafer processing units at startup compared to total throughput. The MIT team of Anand [1], Daigle and Ismail [2] were brought in to assess methods of improving this metric. Several feasible approaches were outlined in Chapter 2. The first method involved re-categorizing Quality Notifications (the standard method

of documenting a failure) by failure mode when identifying quality trends. This approach is detailed in Ismail's thesis work [2]. Statistical analysis also suggested that reduction of piece part and assembly shortage occurrences during construction of the final module units should reduce the manufacturing error rate and improve First Pass Yield. Chapter 3 details the MIT team's approach to this solution. The MIT team concluded that by re-calculating the inventory levels of two kanban systems, shortage occurrences for parts procured on this system could be dramatically reduced. By selecting a 97% service level reorder point policy for the kanban piece parts (KC part type procurement), the shortage occurrence frequency of parts on this system could be reduced by 80% from present levels. However, this suggestion would result in a 35% increase in inventory of parts procured in this way. Inventory holding costs would increase by approximately \$320,000 (19%). As for the Gold Square kanban system for holding completed Supermarket assemblies, the MIT team recommends a 99% service level. However, making this change would require an unreasonable increase in inventory over present due to the long lead time required to replenish assemblies on this inventory management system. The MIT team recommends that Applied Materials work to reduce the lead time to build assemblies in the Supermarket, thus allowing lower inventory levels to be maintained on the Gold Square system. By reducing total lead time to 3 days for assemblies on the Gold Squares and upholding a 99% service level for these assemblies, Applied Materials could expect to see a 74% reduction in shortage occurrences.

Chapter 4 details the Supermarket Lead Time reduction project carried out at Applied Materials. A Value Stream Mapping process revealed that only about 7.75 hours of an approximately 5-6 day lead time for Supermarket assemblies could be considered value-added work. It became clear, however, that among other issues, the Supermarket assembly area had too little worker capacity to significantly reduce the lead time for its assemblies. A computer simulation was run to observe the effects of a mixed product workload with varying worker certifications to build assemblies on the lead time. In order to reach a 3 day lead time for assemblies coming from the Supermarket, an approximately 50% increase in human worker capacity would

be required. However, following this recommendation would yield a drop in lead time from 5-6 days currently to, on average, 1.8 days. Seldom would a Supermarket assembly take more than the 3 day lead time threshold to build. This capacity increase would allow the inventory reorder point policy to be successful and more cost-efficient.

7.2 MIT Lincoln Laboratory Engineering Groups

The MIT Lincoln Laboratory is a federally funded research and development center that applies advanced technology to problems of national security. A Federally Funded Research and Development Center (FFRDC) is a not-for-profit organization funded by the U.S. Government to meet long-term research and development needs that cannot be met as effectively by existing in-house or contractor resources. In order to meet its mission, the Lincoln Laboratory has outfitted itself with highly capable mechanical and electronic fabrication shops. These shops are capable of fabricating and assembling anything from satellites to laser communications systems in low volume. However, requests for fabrication from these shops are paperwork heavy and inefficient. As part of a Model Based Enterprise initiative aimed to, among many other goals, improve information re-use, speed up business processes such as fabrication requests, and capacity plan based on upcoming fabrication work at the Lab, the project detailed in Chapters 5 and 6 was carried out. A job shop scheduling software called JobPack was configured up and tested for future use as an out-of-the-box method of optimizing the fabrication schedule in the machine shop.

In addition to the setup of the job shop scheduling software, JobPack, historical data was analyzed to improve the accuracy of delivery date quotes for parts to be fabricated in the Lincoln Lab shops. A simulation was used to observe the delay experienced by real scheduled jobs when fictional (simulated) jobs were added to the schedule to mimic unforeseen random events that occur in the Lincoln Lab production environment. The delay-causing events simulated were incorrect estimates of fabrication time, walk-in fabrication requests, personnel (machine operator) illness, and

random machine failures. The delays seen from the optimal completion date for the real fabrication jobs were recorded and plotted. The number of highly-utilized workstations (machines) that a job visits during fabrication was found to be an indicator of the amount of delay a job could see during its time in the shop. Prediction intervals were assigned to the output ranges of delay that a job could see if it visits zero, one, or two highly utilized machines. A 90% upper confidence limit of the possible delay was selected as a Shop Capacity Buffer to add to the completion date of a job to improve the accuracy of the initial quote made by the JobPack scheduling software. The Shop Capacity Buffer was the term chosen to represent the anticipated delay period from the optimal completion date initially provided by JobPack. By selecting a 90% upper confidence limit for the Shop Capacity Buffer, a 90% on time completion rate should be observed. This rate would be a significant improvement from the current on-time completion rate of about 75%. Moving forward, it is recommended that the Lincoln Lab collect real data for use to calculate the Shop Capacity Buffer as opposed to simulation data. In conclusion, a new delivery date quoting process for fabrication requests was proposed that used the JobPack scheduler as well as the Shop Capacity Buffer to arrive at the scheduled completion date.

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